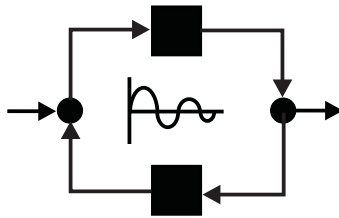


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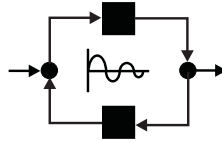
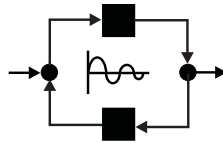


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Enhancement of Multimachine Transient Stability Using Artificial Neural Network Based Phase Shifting Transformer

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Abstract

This paper aims to apply artificial neural network (ANN) based phase shifting transformer (PST) to enhance multi-machine power system transient stability. A new model of the phase shifting transformer based artificial neural network is proposed. The proposed model depends mainly on the function of the phase shifting transformer. The output machine voltages deviations, speed deviations and angles deviations are used as an input signal to the ANN model to provide phase advance for each machine voltage of the studied three machine six bus interconnected power system. The ANN model consists of input layer, hidden layer and output layer. The input layer consists of 6 input signals. The output layer consists of one signal which is the phase advance. The ANN offline training is made first to initialize the weights and bias matrix values. Hence, adaptive function of ANN is used as online ANN application to the studied multimachine power system to modify the weights and bias matrix according to the system dynamic performance. Different fault locations were considered to judge the effectiveness of the proposed ANN based PST. The time simulation results prove that the proposed ANN model based PST is very effective in improving the power system transient stability in case of severe disturbance such as unrepeatable three-phase short circuit fault. A Comparative study between the conventional PST and ANN based PST proves the superiority of the proposed model. The studied power system is modeled and solved using the **MATLAB** software package.

Keywords: Transient Stability enhancement – Multi-machine Power System – Phase shifting transformer – Artificial neural network model.

1.Introduction

Specially designed power system devices can control the flow of the active and/or reactive power in interconnected power systems alleviating line overloads and changing parallel line load sharing. Phase shifting transformer (PST) was the only device capable of controlling both magnitude and direction of the active power flow. Nowadays, the traditional PST is still the most widespread technology[1]. Phase shifting transformer (PST) can provide power flow control in power systems, by varying the phase angle between two buses. The variation of phase angle is carried out by adding a regulated quadrature voltage to the source line to neutral voltage. The use of PST is better than generation rescheduling from the economic point of view[2]. The PST can also be used for power system stability enhancement, and to increase the transmission capacity of the electric power network[3-9]. PST is considered the principle control device that can direct power flow in a specific part of the electric network[10]. The Phase shifting transformer is an electric device from the FACTS (Flexible AC Transmission system) devices[9]. A Proper method to determine the optimal allocation pattern of multiple phase shifting transformers for unwinding parallel flows has been investigated and studied[11]. The specification, design and protection of phase shifting transformers for enhanced interconnected real power system have been studied[12]. Due to growth in electric power networks to a large-scale complicated system, an increase in control system is imposed to meet the global stability improvement. Artificial neural network can be tuned to change system conditions and to provide better control signal than a conventional control approach [13]. The applications of artificial neural networks (ANN) in control, and modeling to



electric power systems have been investigated for different electric devices and different operating power systems parameters[14-20]. The ANN control approach is widely applied to all flexible AC transmission system devices (FACTS). Also, The ANN is used to model the nonlinear loads, wind turbine, and microturbine controller[21-23].

This paper proposes an application of Artificial Neural Networks (ANN) based phase shifting transformer (PST) to improve the transient stability of interconnected multimachine power systems. The PST is modeled based ANN approach. The proposed ANN model can provide the function of the PST and be applied successfully online with the studied multimachine power system. The proposed model of the PST based ANN is simulated with the studied 3-machine 6-bus power system to judge the effect of inserting the proposed ANN based PST in improving the transient stability in case of severe disturbance. The ANN is used first for offline training to obtain the initial values of the weights and bias matrix. Hence adaptive ANN function is applied with the studied system, which provides online ANN based PST. Different fault locations were considered in this study to judge the effect of the proposed approach. The time simulation results proves the effectiveness of insertion of PST based ANN in enhancing the transient stability of the power system in case of severe disturbance such as unrepeated three phase short circuit fault. The comparative study proves the superiority of the proposed ANN based PST over the conventional PST. The study considers that the voltage is constant and just change the phase angle of the phase shift transformer.

2. Studied Power System Model

The multimachine power system used to evaluate the effectiveness of installing Phase Shift Transformer based ANN in enhancing the transient stability is shown in figure 1[24].

A reduced order model is used for this study. An energy function of an electric power system is constructed as a first integral of motion (swing equation). Using the system transient state, the following swing equation can be written as follows[25]:

$$M \frac{d\Delta\omega}{dt} = P_m - P_e - D \frac{d\delta}{dt} \quad (1)$$

$$\frac{d\delta}{dt} = \Delta\omega \quad (2)$$

Where the generator is modeled in the standard simplified way: A constant mechanical power, an electromotive force of constant modulus behind a transient reactance, and lossless transmission system. The modification of a real electric power transfer is given as:

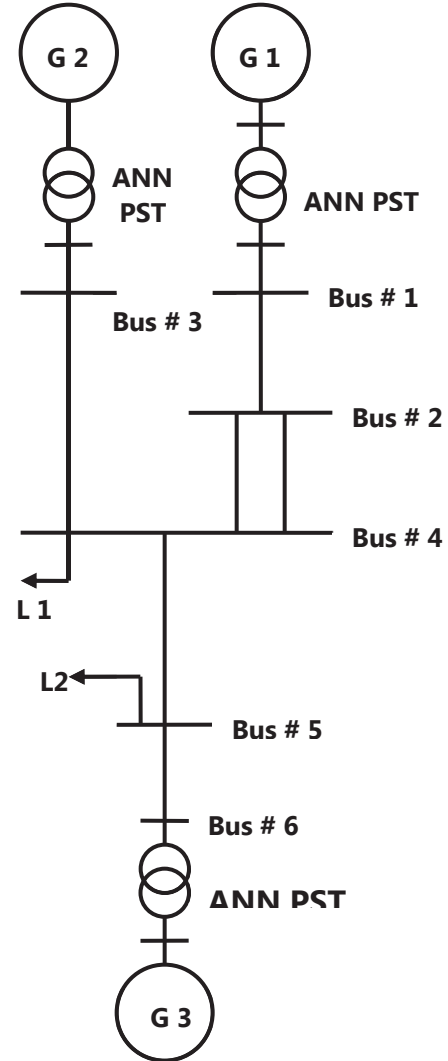


Figure 1 Studied Three-Machine six bus power

$$P_e = \frac{E'V}{X'} \sin(\delta' + \alpha) \quad (3)$$

3. Phase Shifting Transformer

The phase shift transformer controls the active power flow in interconnected power systems by varying the phase angle between two buses. The variation of this phase angle is carried out by adding a regulated quadrature voltage to the source line-to-neutral voltage. PSTs have different forms of characteristics, which are:

- **Direct PST's** are based on one 3-phase core. The phase shift is obtained by connecting the winding in a suitable manner.



- **Indirect PST's** are based on a construction with two separate transformers. One variable tap exciter to regulate the amplitude of the quadrature voltage, and series transformer to inject the quadrature voltage in the right phase.
 - **Unsymmetrical PST's** create an output voltage with an altered phase angle and amplitude compared to the input voltage.
 - **Symmetrical PST's** can create an output voltage with an altered phase angle compared to the input voltage, but with the same amplitude.
- The combination of the previous characteristics can results in 4 categories of PST's. In this study there is only one used and will be discussed in the following paragraph.

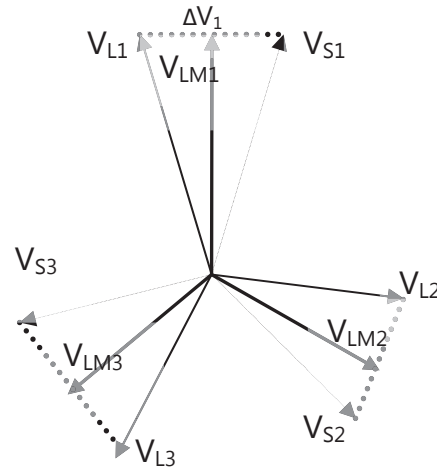


Figure 3. Phasor diagram of a direct,

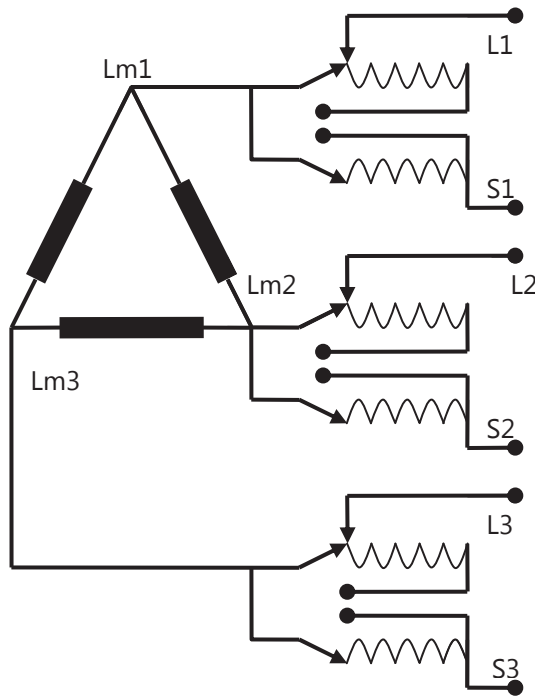


Figure 2 Direct Symmetrical

3.1 Direct Symmetrical PST's[26]

By additional tap changer, the direct unsymmetrical PST can be made symmetrical, the schematic diagram is shown in figure 2. The advantages are increase in maximum attainable angles and that the amplitude voltage remains unchanged. The relation between the angle α and the quadrature voltage is still nonlinear and can be derived from the phasor diagram shown in figure 3.

3.2. Phase Shifting Transformer Model

The phase shift transformer connected between p and q buses can be represented by the equivalent circuit shown in figure 4. [27]. It consists of an admittance in series with an ideal transformer

having a complex turns ratio $\tilde{n} = n \angle \alpha$. The phase angle step size may not be equal at different tap positions. However, equal step size is usually used in power flow and transient stability programs.

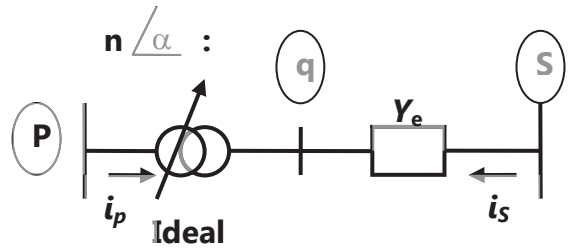


Figure 4 Phase shifting transformer representation

The terminal voltages are related by the following equation:

$$\frac{\tilde{v}_p}{\tilde{v}_q} = n \angle \alpha = n(\cos \alpha + j \sin \alpha) = a_s + j b_s \quad (4)$$

Where α is the phase shift from bus p to bus q, it is positive when $\tilde{v}_p$ leads $\tilde{v}_q$. Since there is no power loss in ideal transformer,

$$\tilde{v}_p \tilde{i}_p^* = -\tilde{v}_q \tilde{i}_s^* \quad (5)$$

Therefore, the transformer current at bus p is:

$$\tilde{i}_p = -\frac{1}{a_s - j b_s} \tilde{i}_s = \frac{Y_e}{a_s - j b_s} (\tilde{v}_q - \tilde{v}_s) \quad (6)$$



Substitute for $\tilde{v}_q$ from the previous equation we can get:

$$\tilde{i}_p = \frac{Y_e}{a_s^2 + b_s^2} [\tilde{v}_p - (a_s + jb_s) \tilde{v}_s] \quad (7)$$

Substitute for $\tilde{i}_p$ the value of $\tilde{i}_s$ can be obtained as the following equation:

$$\tilde{i}_s = \frac{Y_e}{a_s^2 + b_s^2} [-\tilde{v}_p + (a_s + jb_s) \tilde{v}_s] \quad (8)$$

From the previous equation, the phase shifter terminal voltages and currents can be arranged in the following matrix equation as:

$$\begin{bmatrix} \tilde{i}_p \\ \tilde{i}_s \end{bmatrix} = \begin{bmatrix} \frac{Y_e}{a_s^2 + b_s^2} & \frac{-Y_e}{a_s - jb_s} \\ \frac{Y_e}{a_s + jb_s} & Y_e \end{bmatrix} \begin{bmatrix} \tilde{v}_p \\ \tilde{v}_s \end{bmatrix} \quad (9)$$

It is clear that the previous admittance matrix is unsymmetrical, so that the transfer admittance from bus p to s is not equal the transfer admittance from s to p . The previous equation incorporating with the power system model and solved using Matlab software.

4. Neural Network Model of Phase shifting Transformer

To demonstrate the neural network model of the phase shifting transformer, different operating conditions, different fault duration and different fault location are considered to obtain the studied power system performance data. The data obtained are machine terminal voltages magnitude, angle deviations and speed deviation. Hence the neural network construction consists of input, hidden and output layers. The input signals are voltages, speed deviation, angle deviations and the output signal is the phase shift angle.

4.1 Initialize the Neural Network Data

The proposed ANN based PST consists of three layers, named input layers, hidden layer and output layer. The input layer has six nodes. After try and error the best number of hidden layer found as 2 nodes with nonlinear tansigmoid function. The output layer consists of one node. The ANN structure is shown in figure 5. The operation of such ANN can be described as follows[28].

1. The input layer nodes receive the data from the studied power system.
2. The output signals from the input nodes pass to hidden nodes via the weighed links which can be gained or attenuate.

3. Output signals from the hidden nodes result from the input signals passing through their tansigmoid activation function.
4. Hidden layer output signals are sent to output nodes through weighted connections between the hidden nodes and the output nodes.
5. The ANN output signal is obtained using tansigmoid transfer function of the output node.

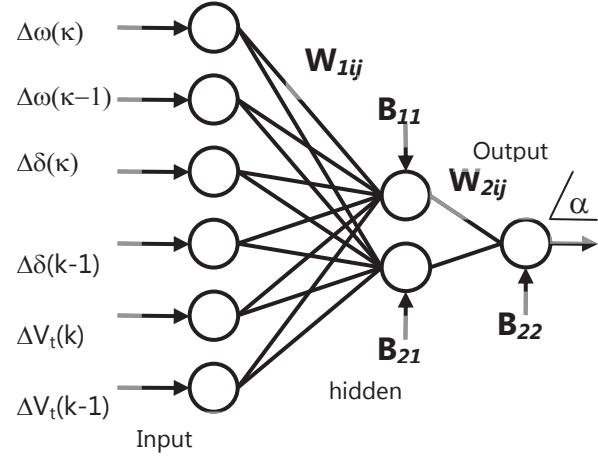


Figure 5 Neural Network Model of PST

The ANN desired output signal is the phase shift angle, where the voltage is considered to be constant value of 1.00 p.u.. The statistical data of the ANN training are as follows:

No. of training data = 2000

No. of iterations = 8000

Sum Squared Error = 0.0001

Learning rate = 0.001

Momentum constant = 0.96

The resulting weight matrix between the hidden and input neurons is given by:

$$W_1 = \begin{bmatrix} 0.9087 & 0.8024 & -0.6704 & 0.3963 & -0.9685 & -0.9532 \\ 0.7601 & -0.9599 & 0.5067 & 0.3897 & -0.6077 & 0.6483 \end{bmatrix}$$

The hidden nodes biases are:

$$B_1 = \begin{bmatrix} -0.8688 \\ -0.3811 \end{bmatrix}$$

The connection weights between the output neurons and the hidden neurons are:

$$W_2 = [-0.5398 \quad 0.1837]$$

The bias of the output neurons is :

$$B_2 = [-0.3144]$$

4.2 Online Neural Network based PST

The input layers receives $\Delta\omega(k)$, $\Delta\omega(k-1)$, $\Delta\delta(k)$, $\Delta\delta(k-1)$, $\Delta V_t(k)$, $\Delta V_t(k-1)$. The back propagation learning algorithm is an interactive method employing the gradient decent algorithm for minimizing the mean square error between the actual output and the target for each pattern in the



training set. The back propagation algorithm can be discussed in the following steps:

1. Initializing the network bias and weight matrix by any values or zeros.
2. Calculating the actual output of the network layers.
3. Updating the network weights in a recursive algorithm starting from the output layer and working backward to the first hidden layer. The weights and biases are updated as:

$$w_{ij}(t+1) = w_{ij}(t) + \Delta w_{ij}(t) \quad (10)$$

$$\theta_j(t+1) = \theta_j(t) + \Delta \theta_j(t) \quad (11)$$

Where:

$$\Delta w_{ij}(t) = \mu \delta_{jp} O_{jp} + \beta \Delta w_{ij}(t-1) \quad (12)$$

$$\Delta \theta_j(t) = \mu \delta_{jp}(t) + \beta \Delta \theta_j(t-1) \quad (13)$$

4. If j is an output layer, then the error will be:

$$\delta_{jp} = F(a_{jp}) * (T_{jp} - O_{jp}) \quad (14)$$

5. If j is a hidden layer then the error will be :

$$\delta_{jp} = F(a_{jp}) * \sum \delta_{jp} w_{ij} \quad (15)$$

Where:

$\Delta w_{ij}(t)$ The weight change from a neuron in the i^{th} layer to the neuron in the j^{th} layer

O_{jp} The network output in the j^{th} unit in the output layer for a pattern p .

T_{jp} Target value in the training pattern

μ The learning rate

w_{ij} The weights from layer i to layer j

β The momentum factor

t The iteration number

θ_j The bias for the layer j

F The sigmoid activation function.

6. Check the error goal. If the condition is valid, keep the recent data of the control system, otherwise start from the beginning.

The previous process is repeated independently for each PST connected directly to each machine.

5. Results and Discussions:

The System under study is shown in figure 1. The parameters of the system are given in Ref.[24]. Firstly, the load flow study is made to obtain the bus voltages and angles at different operating conditions for the transient stability study. The conventional PST is directly connected to each machine, immediately after the three-phase short circuit fault is considered for different intervals and the system is solved to obtain the system performance. The data are saved to be used for the offline training of the proposed ANN. The weights and bias matrix obtained from the offline training are considered as an initial value of the proposed adaptive neural network. The ANN is updated online with the studied system to stabilize the

system under study. The flowchart describing the solution of the system understudy is shown in figure 6.

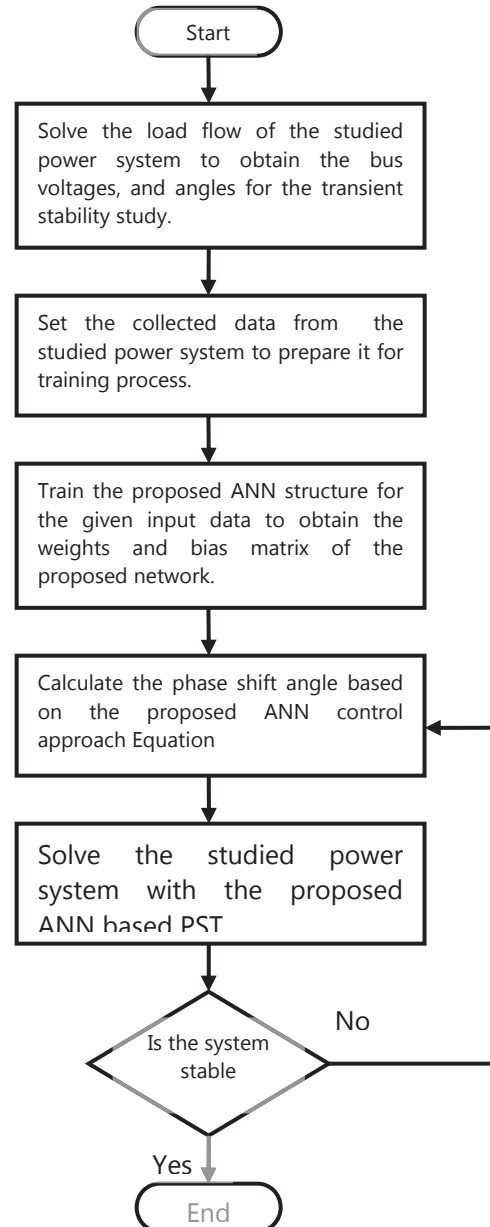


Figure 6 Flowchart of the time simulation of the studied power system with ANN based

To judge the ability of the proposed artificial neural network based phase shifting transformer to improve the transient stability of the studied 3-machine six bus power system in case of severe disturbance. A Comparative study between the dynamic performance of the studied multimachine power system equipped by conventional PST and ANN based PST is obtained. Also the dynamic performance of the studied system without installing PST is given.



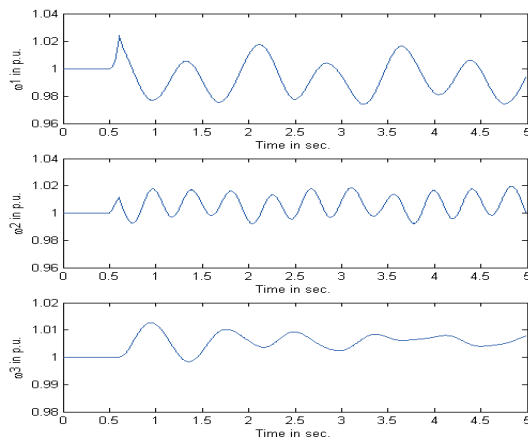


Fig.7 Studied system performance due 3-ph. s.c. fault at bus # 1 without installing PST

5.1. System performance without installing PST

Figures 7, 9 and 11 shows the studied system performance when 3-phase to ground short circuit fault is applied to bus No. 1, 3 and 6 without installing phase shifting transformer. It is very clear that the system is unstable.

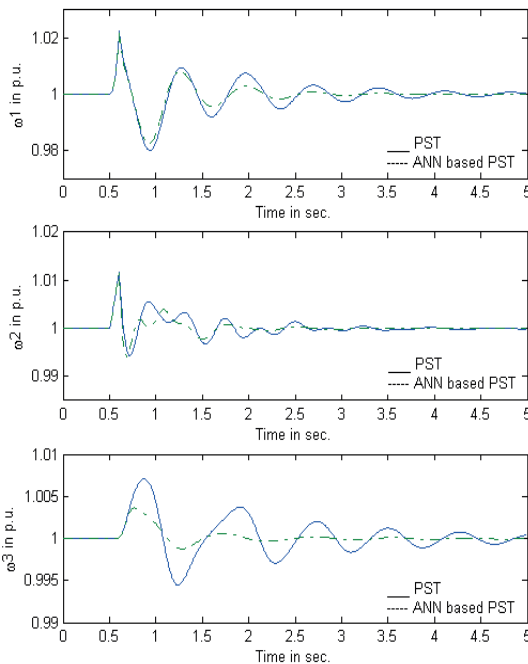


Fig. 8 Studied system performance due 3-ph. s.c. fault at bus # 1 with installing PST and ANN based PST

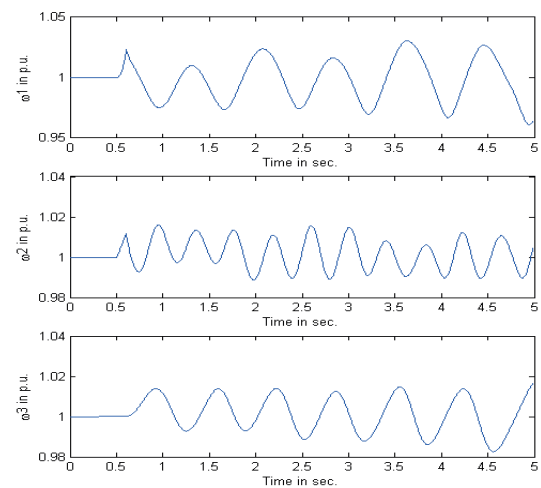


Fig. 9 Studied system performance due 3-ph. s.c. fault at bus # 3 without installing PST

5.2. System performance with installing PST and ANN based PST

Figures 7, 9 and 11 shows the studied system performance when 3-phase to ground short circuit fault is applied to bus No. 1, 3 and 6 with installing conventional phase shifting transformer, and artificial neural network based phase shift transformer. It is very clear that the system is stable with both conventional PST and ANN PST. The comparative study shows that the ANN based PST has better performance than the conventional PST in damping the system oscillations very fast, with less overshoot and undershoot. Also the settling time with installing ANN based PST is very short compared with conventional PST.

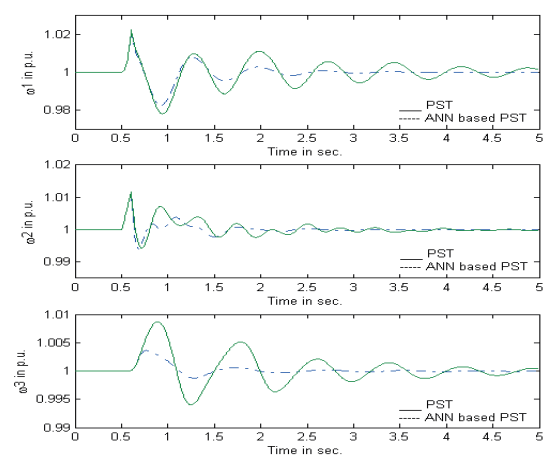


Fig. 10 Studied system performance due 3-ph. s.c. fault at bus # 3 with installing PST and ANN based PST



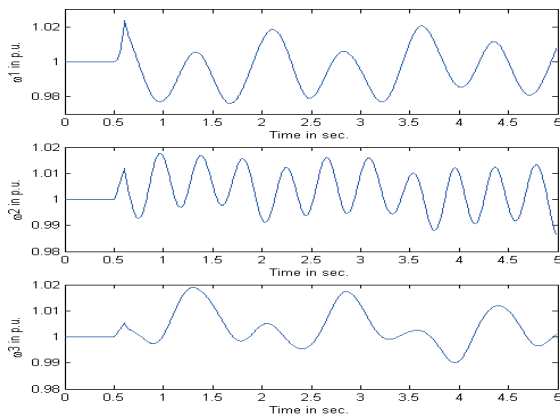


Fig. 11 Studied system performance due 3-ph. s.c. fault at bus # 6 without installing PST

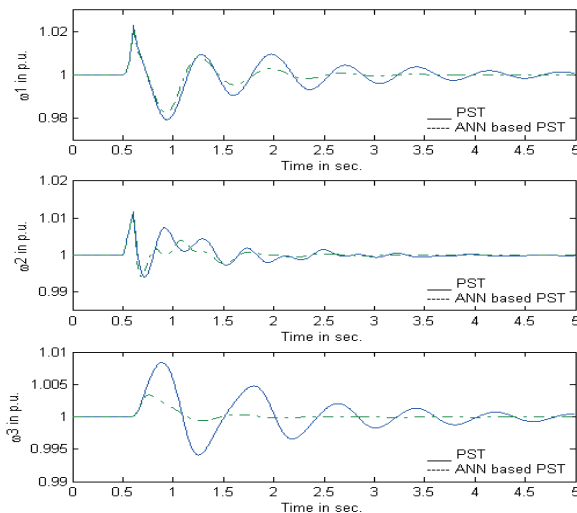


Figure 12 Studied system performance due 3-ph. s.c. fault at bus # 6 with installing PST and ANN based PST

6. Conclusions

This study proposes a novel artificial neural network model for the phase shifting transformer. The studied system performance under different operating conditions, different fault locations and different fault duration time is considered to provide enough data for the neural network training, to ensure a good result of the network parameters. The proposed ANN is constructed and the data is trained to obtain the network parameters. Hence adaptive neural network function is applied. The time simulation proved that the proposed ANN based PST has better performance than that conventional PST with better control quality, less overshoot and under shoot.

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Biography



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Implementing Automated Prediction Systems for Credit Scoring

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Abstract

The aim of credit scoring system is to model or predict the probability that consumers with certain characteristics are to be considered as potential risks. Until recently, the decision to grant credit was based on human judgment to assess the risk of failure to pay. From the literature it has been found that data mining models such as support vector machine (SVM), multilayer perceptron neural network (MLPNN) and decision tree (DT) can help decision makers to improve in this domain. SVM, MLPNN and DT with their remarkable ability to derive meaning from complicated or imprecise data, can be used to extract patterns and detect trends that are too complex to be noticed by either humans or other conventional techniques. This paper evaluates the performance of SVM with polynomial kernel (POLY-SVM), MLPNN with pruning parameters and DT with Chi-squared automatic interaction detection (CHAID) algorithm in the prediction of consumer's credibility. The dataset contains information related to the sociodemographic and financial characteristics of consumers from real world credit bank. Known sets of risky and creditworthy consumer data were used to train the models to categorize new cases. The purpose was to determine an optimum classification model with high predicting accuracy for this problem. Experimental results demonstrate the effectiveness of CHAID-DT model in predicting credit scoring with higher accuracies than other techniques.

Keywords: *Credit scoring, data mining, support vector machine, neural network, decision tree.*

1. Introduction

Normally, consumers who applied for a loan or a credit, have to fill out a questionnaire that asks for relevant financial and personal information. This information is used by a bank (or a financial institution) as the basis for its decision as to whether to lend money or not. Until recently, the decision to grant credit was based on human judgment to assess the risk of failure to pay [3]. Actually, lending to consumers exploded over the last two decades.

Consumer credit has had one of the highest growth rates in any sector of the business. Consumers use credit to acquire goods and services now and then pay for them later. Many credit applicants are, in fact, good credit risks, but some are not. The risk for financial institutions comes from not knowing how to distinguish the creditworthy applicants from the bad ones. There is a need to use more formal and objective methods (generally known as credit scoring) to help credit providers decide whether to grant credit to an applicant. Credit scoring is the set of decision models and their underlying methods that help financial institutions in the granting of consumer credit [4]. The goal of these methods is to predict credit applicants into two classes: the "good credit" or creditworthy class that is liable to reimburse the financial obligation and the "bad credit" or risky class that should be denied credit due to the high probability of defaulting on the financial obligation. The prediction is dependent on sociodemographic characteristics of the consumer (such as age, education level, occupation and income), the repayment performance on previous loans and the type of loan. From the literature it has been found that data mining models such as SVM, MLPNN and DT can help decision maker to improve in this domain [5-7]. They have remarkable ability to derive meaning from complicated or imprecise data, can be used to extract patterns and able to detect trends that are too complex to be noticed by either humans or other conventional techniques. This paper evaluates the performances of SVM with polynomial kernel, MLPNN with pruning parameters and DT with Chi-squared automatic interaction detection in the prediction of consumer's credibility. The three models have been trained on data samples of real world credit dataset from the University of California Irvine (UCI) Machine Learning Repository [1]. The remainder of the paper is organized as follows: Section (2) focuses on the sociodemographic and financial characteristics of consumers and reviews the recent published papers in the credit scoring subject. Section (3) reviews the three classification models and presents their parameters that need to be optimized. Section



demonstrates the experimental results to show the effectiveness of each model. Finally, conclusions are introduced in Section (5).

2. Background

2.1. Credit card dataset

The Australian credit dataset used in this dataset is obtained from the UCI Machine Learning Repository [1]. The dataset consists of 3306 samples. 307 correspond to creditworthy applicants and 303

correspond to risky ones to whom credit requests should be refused. Each sample contains 15 attributes of which 11 attributes are continuous (range) and the remaining attributes are categorical (nominal). In order to preserve the confidentiality of the data, the names and values of the attributes were replaced by meaningless identifiers. Table 1 shows the attributes of the dataset with the number of missing values for each one. The missing values are replaced with the mode or the mean of each attribute.

Table 1. Contents of the Australian credit dataset

Attribute	Type	Values	Number of missing values	Mode/Mean for attributes with missing values
A1	Flag	b, a.	12	b
A2	Range	Continuous.	12	31.57
A3	Range	Continuous.		
A4	Nominal	u, y, l, t	0	u
A5	Nominal	g, p, gg	0	g
A6	Nominal	c, d, cc, i, j, k, m, r, q, w, x, e, aa, ff.	0	c
A7	Nominal	v, h, bb, j, n, z, dd, ff, o.	0	v
A8	Range	Continuous.		
A9	Flag	t, f.		
A10	Flag	t, f.		
A11	Range	Continuous.		
A12	Flag	t, f.		
A13	Nominal	g, p, s.		
A14	Range	Continuous.	13	104.02
A15	Range	Continuous.		
Class	Flag	0, -		

0 missing values are replaced with the mode or the mean of the attribute.

2.2. Previous works

The logistic regression has been for long time the most used statistical model in assessing the credit risk [4, 5]. Afterward, a number of quantitative models are being used also including linear discriminant analysis (LDA) [6], artificial neural network (ANN) [7], ensemble of neural networks [11], decision tree [12], genetic programming [13] and support vector machine [14]. Two recent reviews of these models published in 2007 and 2010 can be found in [8] and [15] respectively. Actually, the issue of credit scoring is attracting several scientists. Search for “credit and scoring” on *sciencedirect* library results in 140 studies in January 2010 and 72 studies published in 2010. In the Egyptian literature, there are two remarkable papers which have been recently published in 2010 and 2011 by Hussein Abdo et al. In [16] they concluded that neural network models gave a better average correct classification rate than conventional techniques such as, discriminant analysis and logistic regression. In [13], they investigated the ability of genetic programming in the analysis of credit scoring models in the Egyptian public sector banks.

3. Classification models

3.1. Decision tree

DT models are powerful classification algorithms. They are becoming increasingly more popular with the growth of data mining applications [5, 8]. As the name implies, this model recursively splits data samples into branches to construct a tree structure for the purpose of improving the prediction accuracy. Each tree node is either a leaf node or decision node. All decision nodes have splits, testing the values of some functions of data attributes. Each branch from the decision node corresponds to a different outcome of the test. Each leaf node has a class label attached to it. Figure 1 shows an illustrating example for binary tree where each decision node has two splits only. CHAID-DT model allows multiple splits on a predictive attribute. This model relies on the Chi-square χ^2 test to determine the best split at each step. CHAID-DT only accepts nominal or ordinal categorical predictive attributes [16]. When predictors are continuous, they are transformed into ordinal ones. Ordinal attribute is ordered set with intrinsic ranking.



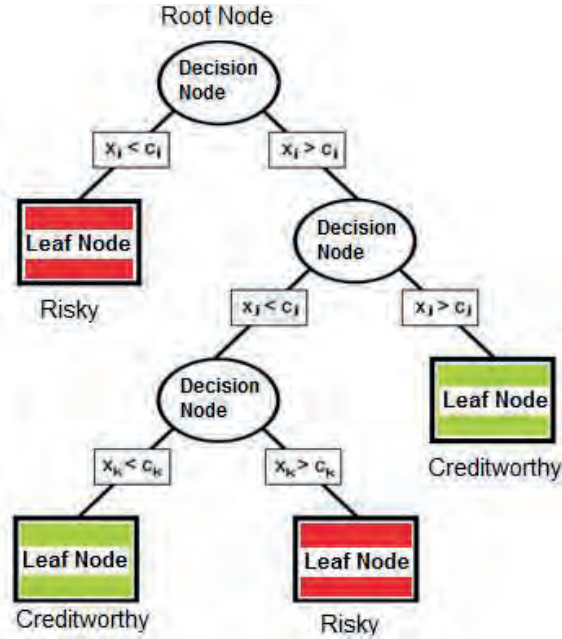


Figure 1. Example of a binary decision tree.

The CHAID-DT modeling algorithm is as follows [17]:

1. Binning the continuous attribute (if exists) to create a set of categories, where each category is a subrange along the entire range of the attribute. This binning operation permits CHAID-DT model to accept both categorical and continuous inputs, although it internally works only with categorical ones.
2. Analyzing the categories of each attribute to determine which ones can be merged safely to reduce the number of categories.
3. Computing the adjusted p value for the merged categories by applying Bonferroni adjustments.
4. Searching for the split point with the smallest adjusted p value (probability value, which can be related to significance) to find the best split.

In step 2, the algorithm merges values that are judged to be statistically homogeneous (similar) with respect to the target attribute and maintains all other values that are heterogeneous (dissimilar). If the p value is greater than specified parameter α_{merg} then the algorithm merges the pair of categories into a single one. The value of α_{merg} must be greater than 0 and less than or equal to 1. To prevent any merging of categories, specify a value of 1. In step 4, each predictive attribute is evaluated for its association with the target attribute, based on the adjusted p value of the statistical test of association. The predictive attribute with the strongest association, indicated by the *smallest* adjusted p value, is compared to a pre-specified split threshold α_{split} . If the adjusted p -value is less than or equal to α_{split} , that attribute is selected as the split attribute for the current node. After the split is applied to the current node, the child nodes are examined to see if they warrant splitting by applying the merge-split process to each in turn. Processing proceeds recursively until one or more stopping rules

are triggered for every unsplit node, and no further splits can be made. In this study, the target attribute is of categorical type (creditworthy or risky). The Likelihood ratio has been used to compute the chi-square statistic. The algorithm forms a contingency (count) table using the classes of the target attribute as columns and the categories of the predictive attribute as rows. The expected cell frequencies under the null hypothesis of independence are estimated. The observed cell frequencies and the expected cell ones are used to calculate the chi-squared statistic and the p value.

$$\chi^2 = \sum_{i=1}^n \sum_{j=1}^m n_{ij} \ln \left(\frac{n_{ij}}{\hat{m}_{ij}} \right) \quad (1)$$

where $n_{ij} = \sum_n n_{ij}$ ($n = i \wedge n = j$) is the observed cell frequency and $\hat{m}_{ij}$ is the expected cell frequency for cell ($n = i, n = j$), and the p value is computed as follows:

$$p = \Pr(\chi_d^2 > \chi^2) \quad (2)$$

The CHAID-DT model is fast, builds “wider” decision trees as it is not constrained to make binary splits making it very popular in market research. The model can be conveniently summarized in a simple two-way contingency table, with multiple categories for each variable. However, this algorithm requires larger quantities of data to get dependable results.

3.2. Neural network

Multilayer perceptron neural network (MLPNN) with back-propagation is the most popular artificial neural network architecture [17,18]. The MLPNN is known to be a powerful function approximator for prediction and classification problems. It is debatably the most commonly used and well-studied ANN architecture. Figure 2 shows structure of MLPNN which is organized into layers of neurons input, output and hidden layers. There is at least one hidden layer, where the actual computations of the network are processed. Each neuron in the hidden layer sums its input attributes x_i after multiplying them by the strengths of the respective connection weights w_{ij} and computes its output using activation function (AF) of this sum. AF may range from a simple threshold function, or a sigmoidal, hyperbolic tangent, or radial basis function.

$$y_i = f \left(\sum w_{ij} x_j \right), \quad (3)$$

where f is the activation function.

Back-propagation (BP) is a common training technique for MLPNN. The available dataset is normally divided into training and test subsets. BP works by presenting each input sample to the network where the estimated output is computed



by performing weighted sums and transfer functions. The sum of squared differences between the desired and actual values of the output neurons is defined as

$$= \frac{1}{2} \sum (d -)^2 \quad (4)$$

where d is the desired value of output neuron and is the actual output of that neuron.

Weights w_i in Equation (3), are adjusted to reduce the error of Equation (4) as fast, quickly as possible. BP applies a weight correction to reduce the difference between the network outputs and the desired ones i.e., the neural network can learn, and can thus reduce the future errors. The performance of MLPNN depends on network parameters, the network weights and the type of transfer functions used [1].

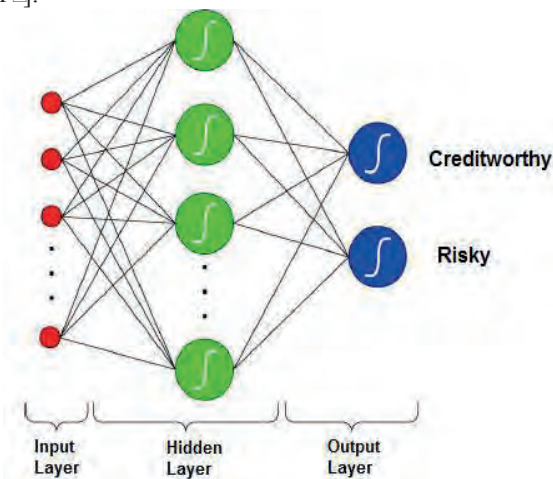


Figure 2. The structure of multilayer perceptron neural network.

When using an MLPNN, three important issues need to be addressed—the selection of data samples for network training, the selection of an appropriate and efficient training algorithm and determination of network size. New algorithms for data portioning [2] and efficient training with faster convergence properties and less computational requirements are being developed [21]. However, the third issue is a more difficult problem to solve. It is necessary to find a network structure small enough to meet certain performance specifications. Pruning methods for improving the input-side redundant connections were also developed that resulted in smaller networks without degrading or compromising their performance [22].

3.3. Support vector machine

The support vector machine is a supervised machine learning technique, which is based on the statistical learning theory. It was firstly proposed by Cortes and Vapnik from his original work on structural risk minimization in [24] and modified by Vapnik in [25]. The algorithm of SVM is able to create a complex

decision boundary between two classes with good classification ability. The basic idea is to map the data into a higher dimensional feature space via a nonlinear mapping kernel function chosen a priori (Figure 3), and constructs a hyperplane, which splits class members from non-members (Figure 4).

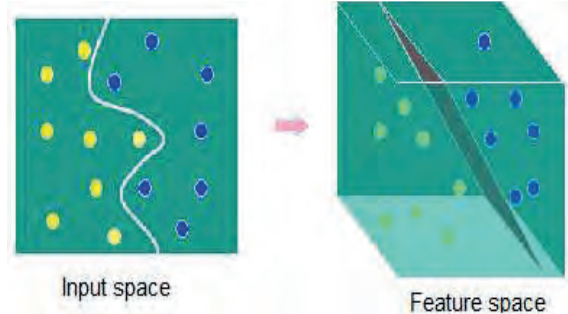


Figure 3. Mapping kernel.

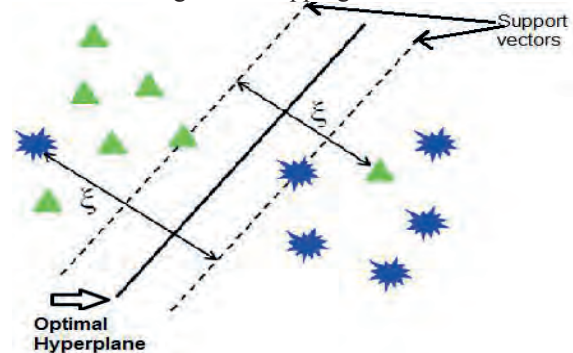


Figure 4. Optimal hyperplane.

SVMs introduce the concept of 'margin' on either side of a hyperplane that separates the two classes. Maximizing the margins and thus creating the largest possible distance between the separating hyperplane and the samples on either side, is proven to reduce an upper bound on the expected generalization error. SVM may be considered as a linear classifier in the feature space. On the other side it becomes a nonlinear classifier as a result of the nonlinear mapping from the input space to the feature one [2, 27]. For linearly separable classes, SVM divides these classes by finding the optimal (with maximum margin) separating hyperplane. Optimal hyperplane can be found by solving a convex quadratic programming (QP) problem [5]. Once the optimum separating hyperplane is found, data samples that lie on its margins are known as support vectors. The solution to this optimization problem is a global one. For linearly decision space, suppose the training subset consists of n samples $(x_1, y_1), \dots, (x_n, y_n) \in \mathbb{R}^p$ and $y_i \in \{-1, 1\}$ i.e. the data contains only two classes. The separating hyperplane can be written as

$$(x_i) = w \cdot x_i + b \quad (5)$$

where the vector w and constant b are learned from a training subset of linearly separable samples. The solution of SVM is equivalent to solve a linearly constrained quadratic programming problem as Equation (5) for both targets -1 and 1 .



$$i = w_i + \geq 1, i=1, \dots, n. \quad (6)$$

As mentioned before, samples that provide the above formula in case of equality are referred as support vectors. SVM classifies any new sample using these support vectors. On the other hand, margins of the hyperplane follow the subsequent inequality

$$\frac{w \cdot x}{\|w\|} \geq \Gamma, i=1, \dots, n. \quad (7)$$

The norm of the w has to be minimized in order to maximize the margin Γ . In order to lessen the number of solutions to the norm of w , the following equation is assumed

$$\Gamma \times \|w\| = 1 \quad (8)$$

Then the algorithm tries to minimize the value of $\frac{1}{2}\|w\|^2$ subject to the condition (8). In the case of non-separable samples, slack parameters ξ are added into the condition as follows.

$$i(w_i + \xi) \geq 1 - \xi, \xi \geq 0 \quad \forall i \quad (9)$$

And the value that we want to minimize becomes:

$$C \sum_{i=1}^n \xi_i + \frac{1}{2} \|w\|^2. \quad (10)$$

C is a regularization parameter to determine the level of tolerance the model has, with larger C values allowing larger deviations from the optimal solution. This parameter is optimized to balance the classification error with the complexity of the model. There is a family of kernel functions that may be used to map input space into feature space. They range from simple linear and polynomial mappings to sigmoids and radial basis functions. Once a hyperplane has been created, the kernel function is used to map new samples into the feature space for classification. This mapping technique makes SVM dimensionally independent, whereas other machine learning techniques are not. In this study, we used the polynomial function kernel to map the input space into the higher dimensional feature space. Polynomial kernels can be controlled by adjusting the complexity of the mapping d , the coefficient γ and weight value γ in the kernel function (Equation 11) [2].

$$(x_i, x_j) = (\gamma x_i \cdot x_j + r)^d, \gamma \geq 0 \quad (11)$$

where γ , r and d are the kernel parameters

Consequently, there are four parameters need to be optimized in the polynomial kernel-SVM model C , γ , r and d .

4. Experimental results

Figure 5 shows components of the proposed stream for credit scoring. The stream is implemented in SPSS Clementine data mining workbench using Intel core 2 Dup CPU with 2.00 GHz. Clementine uses client-server architecture to distribute requests for resource-intensive operations to powerful server software, resulting in faster performance on larger

datasets [2]. The software offers many modeling techniques, such as prediction, classification, segmentation, and association detection algorithms. The Australian credit dataset contains 1000 of sociodemographic and financial data records each with 15 attributes and 2 target classes; creditworthy and risky. The whole dataset is divided for training the models, and test them. The training set is used to estimate the model parameters, while the test one is used to independently assess these models. These models are applied again to the entire dataset and to any new data.

Credit cards dataset node is connected directly to an Excel file that contains the source data. The dataset was explored for incorrect, inconsistent or missing data. The missing values are replaced with a mode for nominal attribute or a mean for range one. The range attributes are normalized before the analysis using MLP and SVM models. On the other side, they are kept unchanged for the analysis of DT model.

Data audit node provides a comprehensive first look at the attribute values in an easy-to-read matrix that can be sorted and used to generate full-size graphs. The audit node computes different descriptive statistics and histogram of each attribute in the dataset.

Type node specifies the field metadata and properties that are important for modeling and other works in Clementine. These properties include specifying a usage type, setting options for handling missing values, as well as setting the role of an attribute for modeling purposes—input or output. As previously stated, the first 15 attributes in Table 1 are defined as input (predictive) attributes and the credibility of a consumer is defined as target class. Predictive attributes are of mixed types—nominal, flag or range, while the target class is of type flag.

Partition node is used to generate a partition field that splits the dataset into separate subsets for the training and test the models. In this study the dataset was partitioned by the ratio 7:3 for training and test subsets respectively.

CHAID classifier node is trained using the significance of a statistical test as a criterion. The modeling algorithm evaluates all of the values of each potential predictive attribute. The chi-square statistic is computed using the *likelihood* ratio to merge values that are judged to be statistically homogeneous with respect to the target attribute. After merging similar categories, the algorithm selects the best predictive attribute to form the first branch in the decision tree, such that each child node is made of a group of homogeneous values of the selected attribute. The best values of α_{merge} and α_{split} are found to be 0.15 for both and the maximum allowable depth is set to 5. The resulting accuracies for training and testing are 0.84 and 0.77 respectively. CHAID-DT model is very fast—it takes below one second to build the model and easy to interpret—it can be expressed as a set of rules (Figure 6).



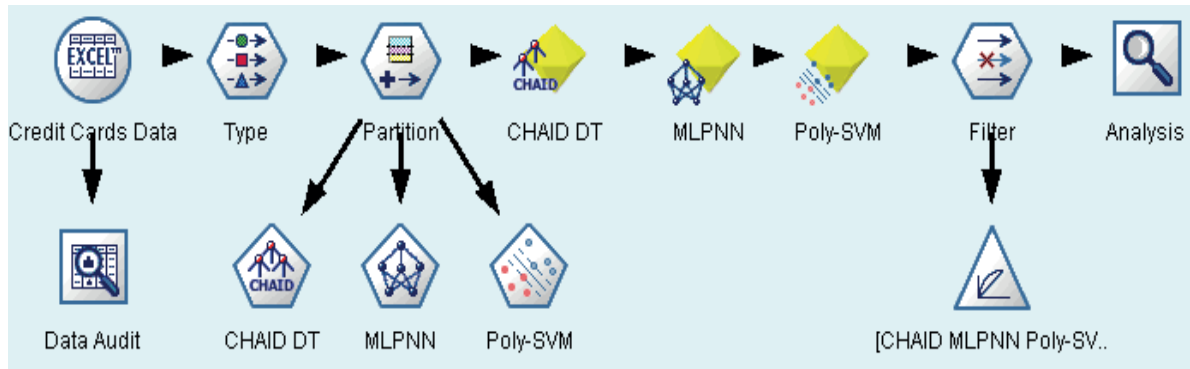


Figure 5. Stream of classification models for credit scoring system.

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if (A□ in [ □□ ])
    if (A13 in [ □□ ])
        if (A1□ in [ □□ ]) □□ Risky (cases 220; accuracy 0.945)
        if (A1□ in [ □□ ]) □□ Risky (cases 65; accuracy 0.985)
        if (A13 in [ □□ ]) □□ Creditworthy (cases 8; accuracy 0.625)
        if (A13 in [ □□ ]) □□ Risky (cases 36; accuracy 0.861)
    if (A□ in [ □□ ])
        if (A1□ in [ □□ ])
            if (A15 □□ □□)
                if (A14 □□ 12□)
                    if (A4 in [ □□ ]) □□ Creditworthy (cases 27; accuracy 0.926)
                    if (A4 in [ □□ ]) □□ Risky (cases 9; accuracy 0.667)
                    if (A14 □ 12□ and A14 □□ 1□□) □□ Risky (cases 12; accuracy 0.833)
                    if (A14 □ 1□□ and A14 □□ 3□5 )
                        if (A13 in [ □□ ]) □□ Creditworthy (cases 21; accuracy 0.619)
                        if (A13 in [ □□ ]) □□ Risky (cases 10; accuracy 0.7)
                        if (A14 □ 3□5) □□ Risky (cases 12; accuracy 0.833)
                if (A15 □□ and A15 □□ □□)
                    if (A4 in [ □□ ])
                        if (A14 □□ 15□) □□ Risky (cases 7; accuracy 0.714)
                        if (A14 □ 15□) □□ Creditworthy (cases 8; accuracy 0.□75)
                        if (A4 in [ □□ ]) □□ Risky (cases 8; accuracy 0.75)
                        if (A4 in [ □□ ]) □□ Creditworthy (cases 19; accuracy 0.947)
                    if (A15 □□ □□)
                        if (A1□ in [ □□ ])
                            if (A15 □□ 4 )
                                if (A11 □□ 4) □□ Creditworthy (cases 32; accuracy 0.781)
                                if (A11 □ 4 ) □□ Creditworthy (cases 28; accuracy 1.00)
                            if (A15 □ 4 and A15 □□ 237)
                                if (A4 in [ □□ ]) □□ Creditworthy (cases 32; accuracy 0.781)
                                if (A4 in [ □□ ]) □□ Risky (cases 8; accuracy 0.5)
                            if (A15 □ 237 and A15 □□ 2,□□□) □□ Creditworthy (cases 84; accuracy 0.964)
                            if (A15 □ 2,□□□) □□ Creditworthy (cases 44; accuracy 1.00)

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Figure □ The generated rule set of CHAID-DT model; this rule set sufficient for correct prediction of 89.88% of the training samples and □□7□□ of the test ones.

MLPNN classifier node is trained using the pruning method. It begins with a large network and removes the weakest neurons in the hidden and input layers as training proceeds. To prevent overtraining, portion of the training subset has been used as a validation subset. The network is trained on the rest of training subset, and accuracy is estimated based on the validation subset. The stopping criterion is set

based on time□ the network is trained for one minute. However, the training process may be interrupted at any point to save the network model with the best accuracy achieved so far. Using the Australian credit scoring dataset, the resulting structure consists of four layers□ one input, one hidden layer and the output layer with 3□ 2 and 1 neurons respectively. The prediction accuracies of training and test samples are



7 and 1 respectively. These results assured the conclusion of [2] where they empirically stated that given the right size and the structure, the MLPNN is capable of learning arbitrarily complex nonlinear functions to arbitrary accuracy levels.

Poly-SVM classifier node is used to train SVM with polynomial kernel. This model has four parameters that need to be optimized C , γ , r and d . The value of the regularization parameter C should be set between 1 and 10 inclusive; increasing the value improves the prediction accuracy for the training data, but this can

also lead to overfitting. Using trial and error we found that the best values for these parameters are 1, 1, 1 and 11 for C , γ , r and d respectively. These values result in 5.5 and 41 prediction accuracies for training and test subsets respectively. It takes only 27 seconds to build this SVM model.

Filter, Analysis and Evaluation nodes are used to select and rename the classifier outputs in order to compute the performance statistical measures and to graph the evaluation charts. Table 2 summarizes the prediction results for the training and test subsets.

Table 2. Prediction results for training and test subsets of Australian credit dataset.

Model		Dataset Partition	
		Training	Test
Poly-SVM	Correct	5.5	41
	Wrong	14.5	13.5
MLPNN	Correct	7	1
	Wrong	3	11
CHAID-DT	Correct	7	7
	Wrong	12	22

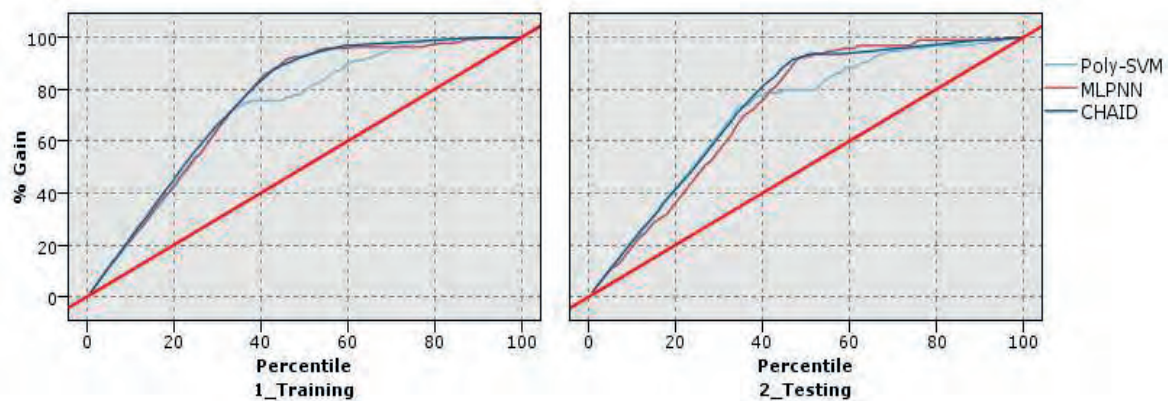


Figure 7. The cumulative gains charts of the three models for training and test datasets.

The gains chart provides a visual summary of the usefulness of the information provided by the models for predicting categorical dependent attributes. The chart summarizes the utility that can be expected by using the respective predictive models, as compared to using baseline information only. The gains charts for Poly-SVM, MLPNN and CHAID-DT models trained in SPSS Clementine for training and test subsets are shown in Figure 7. The higher lines in the gains chart indicate better models, especially on the left side. These charts depict that the performances of the CHAID-DT and MLPNN models are similar for training and test samples and they are better than the performance of Poly-SVM. CHAID-DT model is the best in predicting the test samples with 7 prediction accuracy. MLPNN model is the second best model with 1 accuracy. Poly-SVM model has achieved 41 accuracy. Naturally, these percentages will increase if the

number of training samples increases. When the dataset is partitioned by the ratio 2 for training and test subsets, the CHAID-DT model achieved 2.57 prediction accuracy on test samples.

Sensitivity analysis provides information about the relative importance of the input attributes in predicting the output attribute(s). The basic idea is that the inputs to the classifier are perturbed slightly, and the corresponding change in the output is reported as a percentage change in the output [23]. The first input is varied between its mean plus (or minus) a user-defined number of standard deviations, while all other inputs are fixed at their respective means. The classifier output is computed and recorded as the percent change above and below the mean of that output channel. This process is repeated for each and every input attribute. Figure 8 shows sensitivity analysis of the three models in a graphical format. This graph states that four input



attributes have the most importance; A9, A10, A13 and A14. However, A9 is the most important one with a remarkable difference from

the others. Also CHAID-DT model uses only six attributes out of the available fifteen to conduct a decision about the credibility of a consumer.

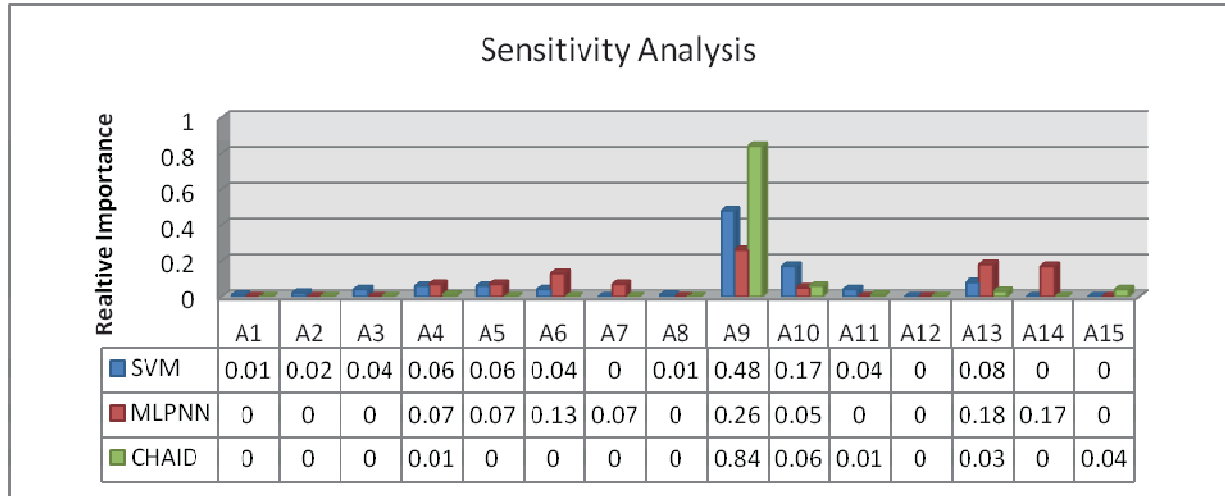


Figure 1 Sensitivity analysis of each classification model.

5. Conclusions

The objective of credit scoring is to help credit providers quantify and manage the financial risk involved in providing credit so that they can make better lending decisions quickly and more objectively. The decision is dependent on sociodemographic and financial characteristics of the consumer (such as age, education level, occupation and income), the repayment performance on previous loans and the type of loan. The automation of this process will result in an increase of the speed and consistency of the loan application process. With the help of automated credit scoring, financial institutions are able to quantify the risks associated with granting credit to a particular applicant in a shorter time. This study evaluated the performance of three data mining methods: support vector machine with polynomial kernel, multilayer perceptron neural network with pruning parameters and decision tree with Chi-squared automatic interaction in the prediction of credit scoring. The dataset contains information from real world credit bank. The dataset was partitioned by the ratio 7:3 for training and test the models. The CHAID-DT model achieved the best prediction accuracy with 77% success on the test samples. This accuracy increased to 82.57%, when the dataset is partitioned by the ratio 8:2. CHAID-DT model is very fast and as all decision trees ones, can be expressed as a set of decision rules. It has the ability to pick and choose among the predictive attributes. Here, it used only six attributes out of fifteen to predict the output. These results recommend that CHAID decision tree model can be used effectively in real world systems to predict the credibility of loan consumers.

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Biography



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SENSORLESS DIRECT TORQUE CONTROL OF INDUCTION MOTOR USING FUZZY CONTROLLER

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Abstract

This paper shows the application of fuzzy logic based duty ratio control technique to reduce torque ripple in an induction motor employing Direct Torque Control (DTC). This technique increases the number of voltage vectors beyond the available eight discrete voltage vectors without any increase in the number of semiconductor switches in the inverter. In addition, this work incorporates Model Reference Adaptive System based observer to estimate rotor speed. Look-up table based on-line tuning PI controller is proposed for outer speed control loop to achieve swift response, less overshooting and precision speed control to have wide torque-speed characteristics. A new algorithm for optimized value of stator flux based on the maximum reference value of electromagnetic torque is proposed to operate in conjunction with duty ratio control. The performance of the proposed drive system is evaluated through digital simulation using MATLAB-SIMULINK package. The simulation results clearly depict the superiority of devised method over the existing methods of DTC.

Keywords: Direct Torque Control, Fuzzy Logic Duty Ratio Control, Induction Motor, Model Reference Adaptive System.

1. Nomenclature

v_{rD}, v_{rQ}	Instantaneous values of the rotor voltage DQ- axes components in the stationary reference frame. (V)
v_{sD}, v_{sQ}	Instantaneous values of the stator voltage DQ- axes components in the stationary reference frame. (V)

$\lambda_{rD}, \lambda_{rQ}$	Instantaneous values of rotor flux linkages DQ-axes components in the stationary reference frame. (wb)
$\lambda_{sD}, \lambda_{sQ}$	Instantaneous values of stator flux linkages DQ-axes components in the stationary reference frame. (wb)
R_s, R_r	Stator and rotor resistance, Ω
L_s, L_r, L_m	Stator, rotor and mutual inductance, H
T_e, T_l	Electromagnetic and load torque, N-m
T_e^*	Reference electromagnetic torque, N-m
$T_{e,ref}^{max}$	Maximum value of reference electromagnetic torque, N-m
P	Number of poles
σ	Inductance leakage factor
δ	Duty ratio
α	Acceleration, radian/sec ²
μ	Degree of membership
ω_{sl}	Slip speed, radian/second
ψ_s	Stator flux, Wb
$\vec{\psi}_s, \vec{i}_s$	Stator flux and current space vector
$ \vec{\psi}_{s,ref} $	Absolute value of Stator flux space vector, Wb
T_r'	Rotor transient time constant
E_{Te}, E_{ψ_s}	Torque and flux error

2. Introduction

The Induction Motor (IM) sensorless speed control replaces the speed sensors by microcomputer or DSP based estimation, which uses machine terminal voltage and current, and thus improves the robustness and reliability of the drive with reduction in cost and complexity. The Model Reference



Adaptive System (MRAS) based speed estimation method is proved as one of the best due to its high performance ability and straightforward stability approach [25]. The IM drives controlled with the vector control method has found wide acceptance in the industry. However, this control technique requires complex coordinate transformation, inner current control loop and accurate system parameters [3]. On the other hand, the Direct Torque Control (DTC) method [7, 12] provides robust and fast torque response without such coordinate transformation, PWM pulse generation and current regulators [20]. Moreover, DTC minimizes the use of motor parameters [7, 10]. Despite, this technique suffers from a major disadvantage of steady state ripple in torque and flux, because none of the inverter-switching vector is able to generate the exact stator voltage at proper instants as well as in space. These torque and flux ripples affect the accuracy of speed estimation; result in high acoustic noise and harmonic losses [26]. There are many methods to reduce this torque and flux ripple: (a) the alternative inverter topologies [11], multilevel inverters [6, 28] and matrix converters [4] which increase the number of switches, and thus cost and complexity; (b) the higher switching frequencies reduce the harmonic content of stator current and thus torque and flux ripple. However, such higher switching frequencies lead to increased switching losses and stress on semiconductor switches of the inverter [22, 23]; (c) yet, another method of reducing torque and flux ripples is space vector modulation [9, 16, 18] that has disadvantage of variable switching frequency [14]. Moreover this method requires complex control schemes than classical DTC and is machine parameter dependent; (d) the Discrete Space Vector Modulation [5, 10] overcomes the disadvantages of SVM technique with an accurate switching table and five level hysteresis bands, but this method cannot guarantee its functionality at low speed range, especially with heavy load [20].

Some more solutions available in literature include modified switching table based DTC [15], variable amplitude control of flux and torque hysteresis bands [13], open loop control of hysteresis band amplitude [27], and fuzzy logic based variable amplitude control of flux and torque hysteresis bands [8]. But these are complex in nature for easy implementation. The ripple in the torque and flux can be easily reduced by applying the selected inverter vector only for the part and not for the

entire switching period unlike that in the classical DTC. This technique, also known as duty ratio control, increases the number of voltage vectors beyond the available eight discrete ones, without any increase in the number of semiconductor switches in the inverter [21, 23]. The work in [2] refers to fuzzy logic duty ratio control but fails to give any details. Similar work presented in [19, 24] claims reduction in ripple to one-third value. However, simulation results were shown for low speed operation only using a fuzzy controller with three membership functions for inputs and output. They have shown an algorithm for optimized value of reference flux based on reference load torque. The work presented in this paper considers the design of new fuzzy logic controller with five membership functions for the inputs & output along with the optimized flux algorithm based on maximum reference value of the electromagnetic torque to adjust the "duty ratio" of inverter switching vectors. The present work shows much better performance (reduced ripple) though it has some similarities with those in [2, 19, 23]. A significant reduction in the ripple than that in [19, 24] has been achieved in the present work, incorporating MRAS and adaptive PI controller. The sensorless mode of operation has been achieved through MRAS based speed estimation. The adaptive PI controller that is based on look-up table is used for outer speed loop for precision speed tracking. A series of simulation tests are conducted using MATLAB-SIMULINK package to validate the performance of the devised algorithm.

The complete paper is organized as follows: Section 3 explains the modelling of induction motor, Section 4 explains strategy of torque ripple minimization. Section 5 discusses design of fuzzy logic duty ratio controller. The simulation results, comparison and discussion are presented in Section 6. Section 7 concludes the work.

3. Modelling of Induction Motor

In DTC the induction motor is modeled in stationary reference frame, thus it does not require any transcendental equations as they require in FOC. Stator and rotor fluxes can be expressed as follows.

$$\lambda_{sD} = \int (v_{sD} - R_s i_{sD}) dt \quad (1)$$

$$\lambda_{sQ} = \int (v_{sQ} - R_s i_{sQ}) dt$$

$$\lambda_{rD} = \int (v_{rD} - R_r i_{rD} - P \omega_m \lambda_{rQ}) dt = \int (-R_r i_{rD} - P \omega_m \lambda_{rQ}) dt$$

$$\lambda_{rQ} = \int (v_{rQ} - R_r i_{rQ} + P \omega_m \lambda_{rD}) dt = \int (-R_r i_{rQ} + P \omega_m \lambda_{rD}) dt$$

[For squirrel cage induction motor $v_{rD} = v_{rQ} = 0$]



Stator and rotor flux linkage equation can be written as follows:

$$\begin{aligned}\lambda_{sQ} &= L_s i_{sQ} + L_m i_{rQ} \\ \lambda_{sD} &= L_s i_{sD} + L_m i_{rD} \\ \lambda_{rQ} &= L_r i_{rQ} + L_m i_{sQ} \\ \lambda_{rD} &= L_r i_{rD} + L_m i_{sD}\end{aligned}\quad (2)$$

Solving the upper set of equations the stator and rotor current equations are derived as follows:

$$\begin{aligned}i_{sD} &= \lambda_{sD} \cdot \frac{L_r}{L_x} - \lambda_{rD} \cdot \frac{L_m}{L_x} \\ i_{sQ} &= \lambda_{sQ} \cdot \frac{L_r}{L_x} - \lambda_{rQ} \cdot \frac{L_m}{L_x} \\ i_{rD} &= \lambda_{rD} \cdot \frac{L_s}{L_x} - \lambda_{sD} \cdot \frac{L_m}{L_x} \\ i_{rQ} &= \lambda_{rQ} \cdot \frac{L_s}{L_x} - \lambda_{sQ} \cdot \frac{L_m}{L_x}\end{aligned}\quad (3)$$

where $L_x = L_s \cdot L_r - L_m^2$

Electromagnetic torque expression of machine is as follows:

$$T_e = \frac{3}{2} \cdot P \cdot [\lambda_{sD} \times i_{sQ} - \lambda_{sQ} \times i_{sD}] \quad (4)$$

The speed can be calculated from the following:

$$T_e - T_L = J \cdot \frac{d\omega_m}{dt} + B \cdot \omega_m \quad (5)$$

4. Torque Ripple Minimization Strategy

Despite of the available complex solutions [4-6, 9-11, 14, 16, 18, 26, 28] the duty ratio scheme presents best remedy to minimal torque and flux ripple, by overshadowing the above-mentioned existing methods. In the classical DTC, a voltage vector is applied for the entire switching period, and this causes the stator current and electromagnetic torque to increase over the whole switching period. Thus for small errors, the electromagnetic torque exceeds its reference value early during the switching period, and continues to increase, causing a high torque ripple. This is then followed by switching cycles, where the null switching vectors are applied to set the electromagnetic torque to its reference value.

The ripple in the torque and flux can be easily

reduced by applying the selected inverter vector only for the part and not for the entire switching period unlike that in the classical DTC IM drive. The time for which an active voltage vector has to be applied is chosen just to increase the electromagnetic torque to its reference value and the null voltage vectors are applied for the rest of the switching period. During the application of the null vectors no power is absorbed by the motor, and thus the electromagnetic torque is almost constant or decreases slightly. But this decrease should be small to have minimum torque ripple. Since this decrease in torque also depends on the modulus of the reference stator flux, an optimized value for the flux has to be used, which is large enough to generate the reference torque. This implies that the maximum electromagnetic torque reference has to be found and the optimized stator flux reference corresponds to this, as follows: The expression of stator current space vector in stator flux oriented reference frame can be obtained as,

$$\bar{i}_s = \frac{(L_m / L_s) |\bar{\psi}_s| (R_r + j\omega_{sl} L_r)}{(R_r + j\omega_{sl} \sigma L_r)} \quad (6)$$

The imaginary part of the above equation gives the torque producing stator current (i_{sy}), and maximum value of this occurs at $\omega_{sl, \max} = 1/T_r'$ (T_r' denotes the rotor transient time constant). By substituting the corresponding $i_{sy, \max}$ value in the electromagnetic torque expression, $T_e = 3/2(P/2) \bar{\psi}_s \times \bar{i}_s$ of induction motor, the maximum torque can be evaluated as follows:

$$T_{e, \max} = 3/2(P/2) |\bar{\psi}_s| i_{sy, \max} \quad (7)$$

The maximum electromagnetic reference torque can be found from the above equation by substituting $T_e = T_{e, \text{ref}}$, as shown in Equation (3).

$$T_{e, \text{ref}}^{\max} = \frac{3}{4} \frac{P}{2} \left(\frac{L_m}{L_s} \right)^2 \frac{|\bar{\psi}_s|^2}{\sigma L_r} \quad (8)$$

The optimized reference flux linkage for the given maximum electromagnetic torque reference can be calculated by setting $|\bar{\psi}_{s, \text{ref}}| = |\bar{\psi}_s|$ as in Equation (4).

$$|\bar{\psi}_{s, \text{ref}}| = \sqrt{\frac{8 T_{e, \text{ref}}^{\max} L_s^2 \sigma L_r}{3 P L_m^2}} \quad (9)$$

When the above optimized stator flux linkage value is used in DTC induction motor drive along with duty ratio control, the torque ripples reduce significantly. But, the duty ratio of each switching



period is a non-linear function of the electromagnetic torque error (E_{Te}), stator flux-linkage error (E_{ψ_s}), and the position of the stator flux-linkage space vector (ρ_s). It is difficult to model such non-linear function. However, the characteristics (such as, model free nature and non-dependence on mathematical equations [17]) of fuzzy logic controller makes the duty ratio determination possible and easier during every switching period.

5. Proposed Methodology

Fig 1 shows the schematic of proposed DTC IM drive with fuzzy logic based duty ratio control. In this paper, two Mamdani type fuzzy logic controllers (FLC-1 and FLC-2) that contain fuzzifier, inference engine, rule base, and defuzzifier are chosen. The FLC-1 and 2 are used for positive and negative flux error respectively. In classical DTC, outer loop speed regulators are conventional PI controllers, which require precise mathematical model of the system and appropriate value of PI constants to achieve high performance drive. Therefore, unexpected change in load conditions or environmental factors would produce overshoot, oscillation of the motor speed, oscillation of the torque, long settling time and, thus causes deterioration of drive performance. To overcome this problem, a look-up table is designed from the experiences of speed response of classical DTC. According to the speed error and change of speed error, the proportional and integral gains are adjusted on-line. The speed can be calculated by the MRAS [1, 25], which uses the motor terminal voltage and current as shown in Fig 1.

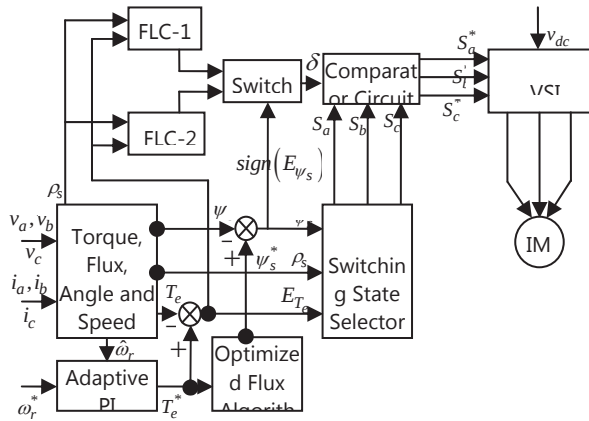


Figure: 1. Schematic diagram of proposed DTC with fuzzy logic duty ratio controller

A. Selection of Input/output Variables

The design starts with assigning mapped input/output variables of FLC. In this work, the first input variable is the torque error ($E_{Te} = T_{e,ref} - T_e$) and the second input variable is the stator flux vector position (ρ_s) at a sampling time t_s . The output variable is duty ratio (δ).

B. Fuzzification

The success of robust fuzzy controller design mainly depends upon this stage. In this stage the crisp variables of the inputs $E_{Te}(t_s)$ and $\rho_s(t_s)$ are converted into fuzzy variables E_{Te} and ρ_s that can be identified by the levels of membership in the fuzzy set. Each fuzzy variable is a member of the subsets with a degree of membership μ varying between 0 (non-member) and 1 (full member).

To make the torque and duty ratio variations smaller, the universe of discourse of torque error and duty ratio are divided into five overlapping fuzzy sets. However, to reduce the complexity of design, the stator flux position is defined with three overlapping fuzzy sets only. The universe of discourse of all the variables, covering the whole region is expressed in per unit values. The fuzzy subsets are defined with triangular membership functions as shown in Fig 2. The linguistic labels are defined as VS=Very Small, S=Small, M=Medium and L=Large, VL=Very Large.

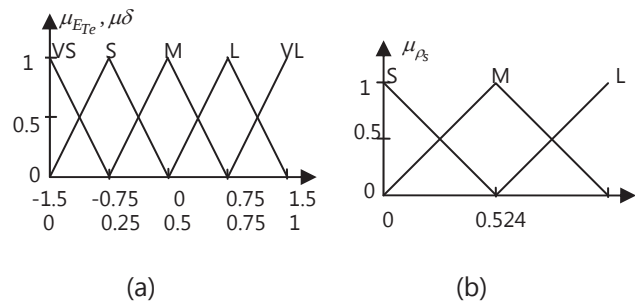


Figure 2: Membership functions for (a) torque error & duty ratio (b) stator flux position.

C. Rule Base and Fuzzy Inference Engine

The Rule base involves defining the rules in IF-THEN form, which govern the relation between input and output variables in terms of membership functions. In this stage the input variables are processed by the inference engine that executes 15 rules (5x3) as shown in Table 1. These rules are generated from the knowledge of control systems and the simulation results of classical DTC induction motor using different switching states.



The inference engine also includes the application of fuzzy operator (AND, OR), product operation of fuzzy implication and maximum aggregation. The relation between different conditions in the same rule is done by means of 'AND' operator. On the other hand, the relationship between different rules is done by means of 'OR' operator.

Table 1: Fuzzy control rules for duty ratio determination

E_{ψ_s}	E_{Te} ρ_s	VS	S	M	L	VL
$ \bar{\psi}_s < \bar{\psi}_{s,ref} $	S	S	M	M	L	VL
	M	VS	S	M	L	VL
	L	VS	S	M	L	VL
$ \bar{\psi}_s > \bar{\psi}_{s,ref} $	S	VS	S	M	M	VL
	M	VS	S	M	L	VL
	L	S	M	L	VL	VL

D. Defuzzification

This stage introduces different inference methods that can be used to produce the fuzzy set values for the output fuzzy variables. In this paper, the center of gravity (COA) or centroid method is used to calculate the final fuzzy value. The COA expression with a discretized universe of discourse can be written as,

$$\delta = \frac{\sum_{i=1}^n \delta_i \mu_{out}(\delta_i)}{\sum_{i=1}^n \mu_{out}(\delta_i)} \quad (5)$$

Where, n denotes the total number of rules. The comparator circuit as shown in Fig 1 compares the duty ratio determined during each switching period with a triangular signal, whose period is equal to that of switching period and thus determines the duration for which active vector should be applied. The modified symmetrical switching vectors fed to the inverter would improve the performance of drive.

6. Results, Comparison and Discussion

A series of simulation tests are conducted on a 4KW, 4pole sensorless inverter-fed IM to evaluate the performance of proposed DTC method.

The simulation results for speed response as well as speed estimation by MRAS are analyzed during transient and steady state conditions. However, the torque response has been analyzed in steady state.

These tests are carried out for high (220rad/sec) and low (50rad/sec) speed operation with sudden drop in load torque from 20N-m to 5N-m at 1.5sec. A constant un-optimized stator flux value of 0.5 Wb is used for classical DTC. Whereas, optimized stator flux values of 0.3734Wb (for 20N-m load) and 0.1867 Wb (for 5N-m load) are used for proposed one.

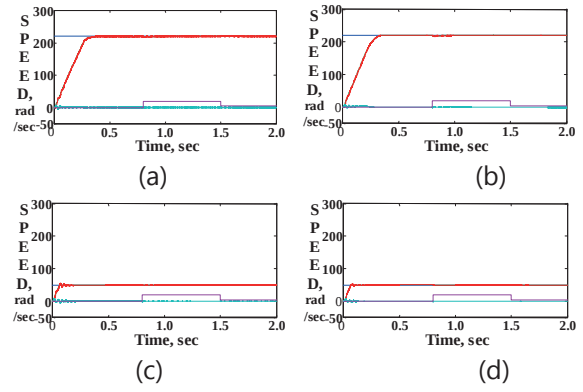


Figure 3: Simulation results for sensorless speed estimation and response due to (a) classical DTC with reference speed of 220rad/sec (b) proposed DTC with reference speed of 220rad/sec (c) classical DTC with reference speed of 50rad/sec, and (d) proposed DTC with reference speed of 50rad/sec.

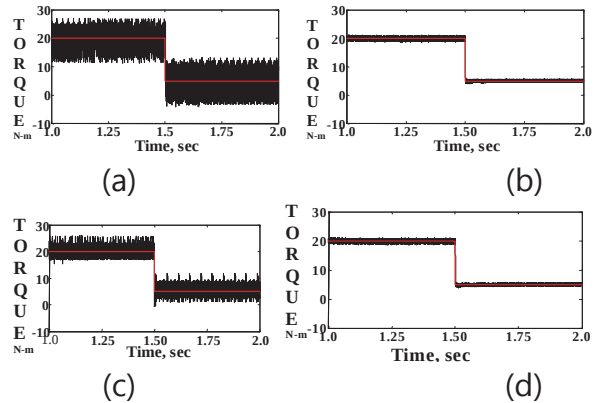


Figure 4: Simulation results for electric torque response due to (a) classical DTC with reference speed of 220rad/sec (b) proposed DTC with reference speed of 220rad/sec (c) classical DTC with reference speed of 50rad/sec, and (d) proposed DTC with reference speed of 50rad/sec

Figure 3(a) and 3(b) shows reference speed of 220rad/sec, measured speed, estimated speed, error between measured and estimated speed, and load torque on a single diagram for classical DTC and proposed DTC respectively. Figure 3(c) and 3(d) show similar result for a reference speed of 50rad/sec. The smoother response for 3(b) and 3(d) against 3(a) and 3(c) respectively, reflects ripple reduction in torque, flux and stator current. As shown in figures, the speed estimator is able to



track the rotor speed under all-operating conditions. The smoother and quicker response with the on-line tuned PI controller for all speed-torque operating range validates its functionality.

Figure 4(a) and 4(b) shows electric torque response for classical DTC and proposed DTC respectively for high speed operation. Figure 4(c) and 4(d) show similar results for low speed operation. In addition to the inherent disadvantage of classical DTC, the constant reference flux causes higher ripple at lower torque level because, the chosen 0.5 Wb is larger than the optimized flux value (0.1867Wbs). But, the proposed method causes lower ripple at lower torque level than at the higher torque level. Moreover, this method is able to eliminate the torque undershoot and overshoots. The average amount of ripple reduction in torque compared to classical DTC is observed to be $1/19^{\text{th}}$ (~11N-m for classical with peaks up to ~16N-m, and ~1.2N-m for proposed) and $1/15^{\text{th}}$ (~15N-m for classical with peaks up to ~19N-m, and ~1N-m for proposed) respectively for higher and lower torque levels of high-speed operation. Similarly, for low speed operation the reduction is observed to be more than $1/10^{\text{th}}$ (~9N-m for classical with peaks up to ~14N-m, and ~0.8N-m for proposed) and $1/17^{\text{th}}$ (~11N-m for classical with peaks up to ~15N-m, and ~0.6N-m for proposed) respectively for higher and lower torque levels.

7. Conclusion

In this paper, three current research topics viz. sensorless control, on-line PI tuning and torque ripple minimization strategy are brought to a common platform to alleviate the disadvantages of classical DTC employed to control an inverter-fed induction motor drive. The fuzzy logic duty ratio controller with optimized reference flux command is applied and verified. Low speed operation of the proposed method dictates the proper functionality of speed estimation as well as precision torque control. From the simulation tests the following justifiable conclusions are drawn against the existing solutions.

1. The devised method is easier to understand, design and implement. The input/output scaling factors for fuzzy logic controller are absent.
2. Increased efficiency as well as lower acoustic noise for the induction motor drive is observed because of the significant reduction ($\sim 1/15^{\text{th}}$) in torque, flux and current ripples/harmonics. In addition to the torque ripple minimization, under (over) shoots are also eliminated.

3. The proposed method operates at a lower switching frequency, and thus reduces switching losses as well as stress on semiconductor switches of the inverter.
4. The proposed algorithm is able to track the actual speed under all operating conditions.
5. During transient conditions the error between measured and estimated speed for fuzzy MRAS is observed to be low when compared to MRAS.

Appendix

3-Phase Induction Motor Parameters

Rotor type: Squirrel cage, Reference frame: Stationary

4KW, 1440 rpm, 50Hz, 4 Poles, $R_s = 1.57\Omega$, $R_r = 1.21\Omega$, $L_s = 0.17\text{ H}$, $L_r = 0.17\text{ H}$, $L_m = 0.165\text{ H}$, $J = 0.06\text{ Kg-m}^2$.

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Extraction, Modelling and Simulation of the Scattering Matrix of a Chebychev Low-Pass Filter with cut-off frequency 100 MHz from its Causal and Decomposed Bond Graph Model

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Abstract

During our studies of the techniques of conception (design) and modelling of linear and nonlinear microwave circuits, we noticed the big need to a method able to improve the analysis and the understanding of circuits, which often function in high frequency. Therefore, we propose, in this paper, a new methodology to study a microwave filter with localized elements (Chebychev low-pass filter) by a joint application of the bond graph approach and the scattering formalism. This study consists of, on the one hand, determining and simulating the scattering parameters of this filter and on the other hand, to modeling the incident and reflected wave propagation since the source towards the load through this filter. In fact, the modelling of these various wave propagation amounts modelling the scattering matrix constituted by the scattering parameters of the studied filter on a particular type of bond graph model often named: "Scattering Bond Graph".

Keywords: *Bond graph modelling, scattering formalism, Chebychev low-pass filter, power wave propagation, and simulation*

1. Introduction

The scattering formalism [1] was used in vast physics fields such as the characterization of the electric circuits. Several work, since the invention of the bond graph approach [2], showed that the scattering formalism constitutes an alternative

approach for the physical systems modelling [3]. They pointed out some properties, and in particular the orthogonality of the scattering matrix [4] or wave matrix [5] which respects intrinsically the causal relations and includes explicitly the conservation laws [6]. In addition, they showed that the scattering representation exists for systems having neither impedance nor admittance such as the junctions of Kirchhoff, the gyrators and the transformers [7].

Moreover, the bond graph language [2] is based on a graphic representation of the physical systems. These representations are based on the identification and the idealization of the intrinsic characteristics of the physical environments and on the structuring of a complex physical system in the networks form [8]. Besides, in physics, the analogies theory allows bond graph technique [2] to generalize the representation networks with all the traditional physics fields of the systems with localized and/or distributed parameters [9].

The proposal of this paper is to apply the scattering formalism [1] and the bond graph technique [2] jointly to build a model able to highlight the incident waves and reflected waves and their propagation on a particular type of bond graph model often named "scattering bond graph" of a Chebychev low-pass filter which functions in high frequency.

At first, we propose to determine the scattering parameters (transmission and reflexion coefficients) of the studied system from its transformed and



reduced bond graph model [10] by the integro-differentials operators [11] which based on the causal ways and algebraic loops present in the causal bond graph model. Then, we will make a simple comparison by simulation of the found scattering parameters and the classic techniques of conception and simulation of the microwave circuits [12] at the aim to validate the founding results.

Finally, we will apply to these scattering parameters a procedure developed and described thereafter to obtain the famous "Scattering bond graph" model [13].

2. Study of LC filters with localized elements

The LC filters are passive filters including only inductances and condensers, in the quadripole form inserted between two terminal resistances: the generator resistance R_1 , and the load resistance R_2 .

There are many topologies to produce these filters of which the most answered is that the LC filters in scale. The LC filters in scale are not any more to show, which is based on the knowledge of the transfer functions and characteristic function corresponding to a specified template [14].

Starting from a transfer function and a characteristic function corresponding to a specified template, it is enough to calculate the various elements L and C for our structure, calculate the entry impedances seen from the two ends of the filter, then, extract the elements (with standardized (normalized) value) in an iterative way. The elements values are calculated by the method known as Darlington method [15].

2.1 Synthesis of LC filter with localized elements

We propose to synthesize a low-pass filter with 100 MHz of cut-off frequency (f_c), sensibility: $k = 0.5$, and attenuation: $A_{\max} = 0.1\text{dB}$, $A_{\min} = 20\text{dB}$.

By choosing a Tchebychev approximation function, we obtain a filter with order 4 whose transfer function is as follows:

$$H(p) = \frac{1}{1.206p^4 + 2.177p^3 + 3.170p^2 + 2.445p + 1} \quad (1)$$

It is about an asymmetrical structure with even order. The extraction according to the Darlington method [15] leads to the standardized (normalized) values below, and corresponds to a Π (pi) structure as figure 1 refers to.

$$\begin{cases} \tau_{C1}=1.1088 \\ \tau_{L1}=1.3062 \\ \tau_{C2}=1.7704 \\ \tau_{L2}=0.8181 \\ \tau_{R1}=0.0001 \\ \tau_{R2}=0.0001 \end{cases} \Rightarrow \Rightarrow \begin{cases} C_1=35.3\text{ pF} \\ L_1=104\text{ nH} \\ C_2=56.3\text{ pF} \\ L_2=65.1\text{ nH} \\ R_1=50\Omega \\ R_2=50\Omega \end{cases} \quad (2)$$

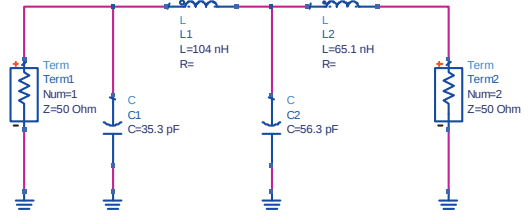


Figure 1: The corresponding Chebyshev low-pass filter.

2.2 Simulation results of the scattering parameters

The traditional tool for simulation of the scattering parameters under HP-ADS software [12], as figure 2 refer to, makes it possible to visualize the filter response in transmission (S_{12} and S_{21}) and in reflexion (S_{11} and S_{22}) on a band frequency surrounding the cut-off f_c as figure 3 refers to.

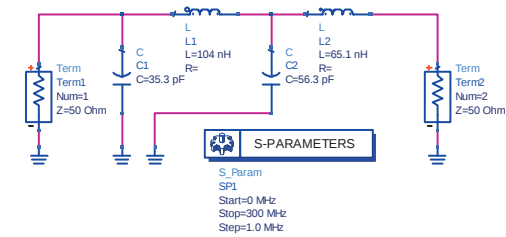


Figure 2: Tchebychev low-pass filter, under HP-ADS software

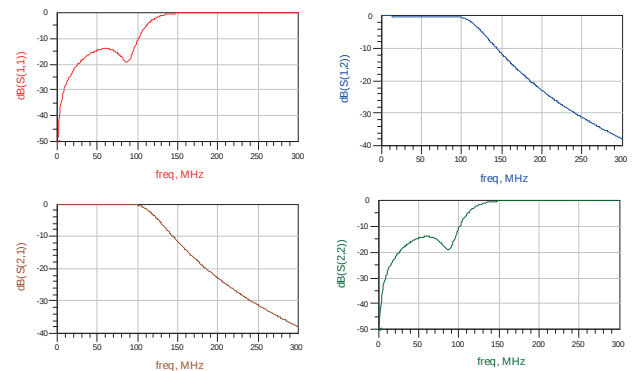


Figure 3: Simulation results of the Tchebychev low-pass filter.

3. Scattering parameters of the filter exploited from its bond graph model

We propose in this part to determine the scattering parameters [4] of the Chebyshev [16] low-pass filter from its transformed and reduced bond graph



model [10] and by paying attention to the causality assignment and to compare the obtained results with the results found previously by the traditional techniques used for the conception of the linear and nonlinear microwave circuits under HP-ADS software [12].

3.1 Relations between wave-scattering matrix and bond graph model

Generally, any physical system exists in the form of a quadripole inserted between two particular ports P_1 and P_2 which respectively represent the entry (source) and the exit (load) of the total system [17]. This system can be represented by a generalized bond graph model transformed and reduced as the figure 4 indicates it.

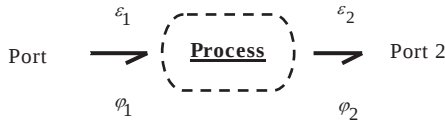
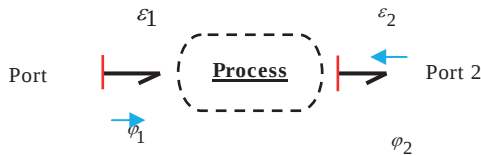


Figure 4: General transformed and reduced bond graph model.

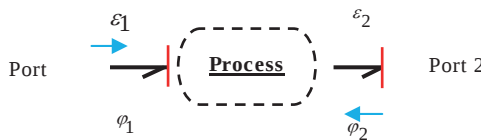
- ε_1 and ε_2 are respectively the reduced variable (effort) at the entry and the exit of the system.
- φ_1 and φ_2 are respectively the reduced variable (flow) at the entry and the exit of the system.

And to establish the entry-exit analytical relations, the bond graph model of the studied system must be transformed, reduced and especially be causal since these relations rest on the concepts of causal way and algebraic loops which exist in the reduced bond graph model [10, 17].

The causality assignment to the reduced bond graph model of figure 4 enables us to notice that they are four different cases of causality assignment in input-output of the process [17].



Case (a)



Case (b)



Case (c)



Case (d)

Figure 5: Different possibilities of causalities assignment.

For each type of reduced and causal bond graph model given by the above figures, we will respectively have the following matrices.

$$\begin{pmatrix} \varepsilon_1 \\ \varphi_2 \end{pmatrix} = \begin{pmatrix} H_{11} & H_{12} \\ H_{21} & H_{22} \end{pmatrix} \begin{pmatrix} \varphi_1 \\ \varepsilon_2 \end{pmatrix} \quad (3)$$

$$\begin{pmatrix} \varphi_1 \\ \varepsilon_2 \end{pmatrix} = \begin{pmatrix} H_{11} & H_{12} \\ H_{21} & H_{22} \end{pmatrix} \begin{pmatrix} \varepsilon_1 \\ \varphi_2 \end{pmatrix} \quad (4)$$

$$\begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \end{pmatrix} = \begin{pmatrix} H_{11} & H_{12} \\ H_{21} & H_{22} \end{pmatrix} \begin{pmatrix} \varphi_1 \\ \varphi_2 \end{pmatrix} \quad (5)$$

$$\begin{pmatrix} \varphi_1 \\ \varphi_2 \end{pmatrix} = \begin{pmatrix} H_{11} & H_{12} \\ H_{21} & H_{22} \end{pmatrix} \begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \end{pmatrix} \quad (6)$$

From the relations given above, we can define the matrix often noted H which gathers the various integro-differentials operators H_{ij} .

$$H = \begin{pmatrix} H_{11} & H_{12} \\ H_{21} & H_{22} \end{pmatrix} \quad (7)$$

H_{ij} represent the integro-differentials operators associated to the causal ways connecting the port P_j to the port P_i and obtained by the general form given below.

$$H_{ij} = \sum_{k=1}^n \frac{G_k \Delta_k}{\Delta} \quad (8)$$

$$\Delta = 1 - \sum L_i + \sum L_i L_j - \sum L_i L_j L_k + \dots + (-1)^m \sum \dots \quad (9)$$

Where:

- Δ = the determinant of the causal bond graph.
- H_{ij} = complete gain between P_j and P_i .
- P_i = input port.
- P_j = output port.
- N = total number of forward paths between P_i and P_j .
- G_k = gain of the k^{th} forward path between P_i and P_j .
- L_i = loop gain of each causal algebraic loop in the bond graph model.



- $L_i L_j$ = product of the loop gains of any two non-touching loops (no common causal bond).
- $L_i L_j L_k$ = product of the loop gains of any three pairwise nontouching loops.
- Δ_k = the cofactor value of Δ for the k^{th} forward path, with the loops touching the k^{th} forward path removed; i.e. Remove those parts of the causal bond graph which form the loop, while retaining the parts needed for the forward path.

We noted that:

$$a_i = \frac{\varepsilon_i + \varphi_i}{2}, \quad b_i = \frac{\varepsilon_i - \varphi_i}{2} \quad (10)$$

$$\varepsilon_i = \frac{V}{\sqrt{R_0}}, \quad \varphi_i = I \sqrt{R_0} \quad (11)$$

These are the reduced voltage and current with respect to R_0 (scaling resistance).

$$\begin{bmatrix} \varepsilon_1 \\ \varphi_1 \end{bmatrix} = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix} \begin{bmatrix} a_1 \\ b_1 \end{bmatrix} \quad (12)$$

$$\begin{bmatrix} \varepsilon_2 \\ -\varphi_2 \end{bmatrix} = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix} \begin{bmatrix} a_2 \\ b_2 \end{bmatrix} \quad (13)$$

$$\begin{bmatrix} b_1 \\ a_1 \end{bmatrix} = \begin{bmatrix} w_{11} & w_{12} \\ w_{21} & w_{22} \end{bmatrix} \begin{bmatrix} a_2 \\ b_2 \end{bmatrix} = [W] \begin{bmatrix} a_2 \\ b_2 \end{bmatrix} \quad (14)$$

According to the preceding equations, we can find, for each case of causality assignment which indicated by figure 5, one wave matrix.

$$W = \begin{bmatrix} \frac{1-H_{11}+H_{22}-\Delta H}{2H_{21}} & \frac{-1+H_{11}-H_{22}-\Delta H}{2H_{21}} \\ \frac{-1-H_{11}-H_{22}-\Delta H}{2H_{21}} & \frac{1+H_{11}-H_{22}-\Delta H}{2H_{21}} \end{bmatrix} \quad (15)$$

$$W = \begin{bmatrix} \frac{1-H_{11}+H_{22}-\Delta H}{2H_{21}} & \frac{1-H_{11}-H_{22}+\Delta H}{2H_{21}} \\ \frac{1+H_{11}+H_{22}+\Delta H}{2H_{21}} & \frac{1+H_{11}-H_{22}-\Delta H}{2H_{21}} \end{bmatrix} \quad (16)$$

$$W = \begin{bmatrix} \frac{1-H_{11}+H_{22}-\Delta H}{2H_{21}} & \frac{-1+H_{11}+H_{22}-\Delta H}{2H_{21}} \\ \frac{1+H_{11}+H_{22}+\Delta H}{2H_{21}} & \frac{1+H_{11}-H_{22}-\Delta H}{2H_{21}} \end{bmatrix} \quad (17)$$

$$W = \begin{bmatrix} \frac{-1+H_{11}-H_{22}+\Delta H}{2H_{21}} & \frac{1-H_{11}-H_{22}+\Delta H}{2H_{21}} \\ \frac{-1-H_{11}-H_{22}-\Delta H}{2H_{21}} & \frac{1+H_{11}-H_{22}-\Delta H}{2H_{21}} \end{bmatrix} \quad (18)$$

$$\Delta H = H_{11}H_{22} - H_{12}H_{21} \quad (19)$$

The scattering parameters are given by the following scattering matrix:

$$\begin{bmatrix} b_1 \\ b_2 \end{bmatrix} = \begin{bmatrix} S_{11} & S_{12} \\ S_{21} & S_{22} \end{bmatrix} \begin{bmatrix} a_1 \\ a_2 \end{bmatrix} = [S] \begin{bmatrix} a_1 \\ a_2 \end{bmatrix} \quad (20)$$

The relations between these matrixes are given by these following equations:

$$\begin{cases} W_{11} = -S_{21}^{-1} * S_{22} \\ W_{12} = S_{21}^{-1} \\ W_{21} = S_{12} - S_{11} * S_{22} * S_{21}^{-1} \\ W_{22} = S_{11} * S_{21}^{-1} \end{cases} \quad (21)$$

And the corresponding scattering matrix is given below:

$$S^{(T)} = \begin{bmatrix} W_{22}^{-1} * W_{12} & W_{11} - W_{21} * W_{12} * W_{22}^{-1} \\ W_{22}^{-1} & -W_{21} * W_{22}^{-1} \end{bmatrix} \quad (22)$$

3.2 Application on the Chebychev low-pass filter

Here, we will try to apply and check the procedure described previously on the Chebychev low-pass filter [16] given by figure 1.

The bond graph model of this filter is given by figure 6.

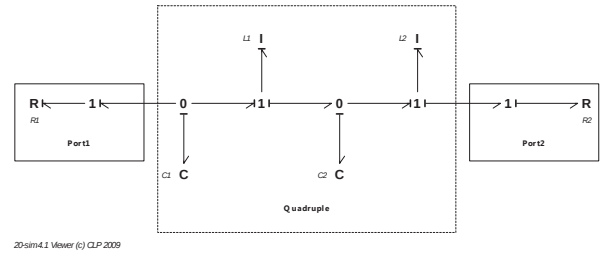


Figure 6: The corresponding bond graph model.

To extract the scattering parameters [4] from the bond graph representation and by using the new method which is described previously; we must transform the bond graph model given by figure 6 into a causal bond graph model often named reduced bond graph model [10] only containing the decomposition junction (1-junction or 0-junction) and the reduced variables with respect to a scaling resistance R_0 (internal source resistance).

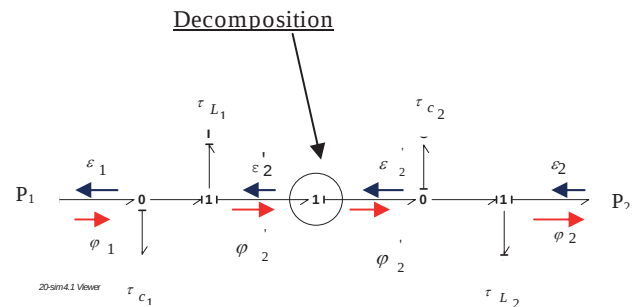


Figure 7: The reduced bond graph model.



Where:

$$\tau_{C_i} = R_0 * C_i \quad (23)$$

$$\tau_{L_i} = \frac{L_i}{R_0} \quad (24)$$

By decomposition the reduced bond graph given by figure 7, we will have the following bond graph representation:

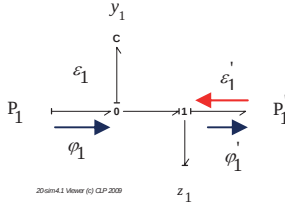


Figure 8: The first sub-model

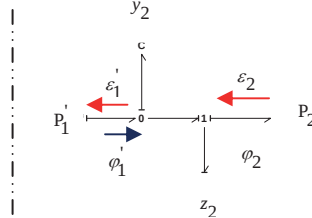


Figure 9: The second sub-model

Notice that:

- z_i : the reduced equivalent impedance of the i element put in series.
- y_i : the reduced equivalent admittance of the i element put in parallel.

So we have:

$$z_1 = \tau_{L_1} * p \quad (25)$$

$$z_2 = \tau_{L_2} * p \quad (26)$$

$$y_1 = \tau_{C_1} * p \quad (27)$$

$$y_2 = \tau_{C_2} * p \quad (28)$$

p : The Laplace operator.

The two sub-models are in conformity with case (a) described previously. So we have the integro-differential operators by taking into account to the previously equations.

$L_1 = \frac{-1}{z_1 y_1}$: Loop gain of the algebraic loop given by the first sub-model.

$L_2 = \frac{-1}{z_2 y_2}$: Loop gain of the algebraic loop given by the second sub-model.

$\Delta_1 = 1 + \frac{1}{z_1 y_1}$: Determinant of causal bond graph of the first sub-model.

$\Delta_2 = 1 + \frac{1}{z_2 y_2}$: Determinant of causal bond graph of the second sub-model.

$$\begin{cases} H_{11} = \frac{z_1}{z_1 y_1 + 1} \\ H_{12} = \frac{z_1 y_1 + 1}{1} \\ H_{21} = \frac{z_1 y_1 + 1}{z_1 y_1 + 1} \\ H_{22} = \frac{-y_1}{z_1 y_1 + 1} \\ \Delta H = \frac{-1}{z_1 y_1 + 1} \end{cases} : \text{The all integro-differential operators of}$$

the first sub-model.

$$\begin{cases} H_{11} = \frac{z_2}{z_2 y_2 + 1} \\ H_{12} = \frac{z_2 y_2 + 1}{1} \\ H_{21} = \frac{z_2 y_2 + 1}{z_2 y_2 + 1} \\ H_{22} = \frac{-y_2}{z_2 y_2 + 1} \\ \Delta H = \frac{-1}{z_2 y_2 + 1} \end{cases} : \text{The all integro-differential operators}$$

the second sub-model.

From these operators, we can deduce directly the wave matrix of the first and second sub-model by taking into account to equations of case (a):

$$W^{(1)} = \frac{1}{2} \begin{bmatrix} z_1 y_1 - z_1 - y_1 + 2 & -z_1 y_1 + z_1 + y_1 \\ -z_1 y_1 - z_1 + y_1 & z_1 y_1 + z_1 + y_1 \end{bmatrix} \quad (29)$$

$$W^{(2)} = \frac{1}{2} \begin{bmatrix} z_2 y_2 - z_2 - y_2 + 2 & -z_2 y_2 + z_2 + y_2 \\ -z_2 y_2 - z_2 + y_2 & z_2 y_2 + z_2 + y_2 \end{bmatrix} \quad (30)$$

The wave matrix of the complete system can be given by the product of the first and the second wave matrix such us:

$$W^{(T)} = W^{(1)} * W^{(2)} = \begin{bmatrix} W_{11} & W_{12} \\ W_{21} & W_{22} \end{bmatrix} \quad (31)$$

From this matrix we can deduce these following scattering parameters:

$$S_{11} = \frac{z_1 z_2 y_1 y_2 + z_1 y_2 (y_1 - z_2) + z_1 (y_1 - y_2 - 1) + z_2 (y_1 + y_2 - 1) + y_1 + y_2}{d(p)} \quad (32)$$

$$S_{12} = S_{21} = \frac{2}{d(p)} \quad (33)$$

$$S_{22} = \frac{-z_1 z_2 y_1 y_2 + z_1 y_2 (y_1 - z_2) + z_1 (y_2 - y_1 - 1) - z_2 (y_1 + y_2 - 1) + y_1 + y_2}{d(p)} \quad (34)$$

$$d(p) = z_1 z_2 y_1 y_2 + z_1 y_2 (y_1 + z_2) + (z_1 + z_2)(y_2 + y_1) + (z_1 + z_2) + (y_1 + y_2) + 2 \quad (35)$$

3.3 Simulation results of the scattering parameters

A simple programming and simulation of the following scattering parameters equations, give the figure 10, figure 13, figure 11 and figure 12 below which represent respectively the reflexion and transmission coefficients of the studied filter.

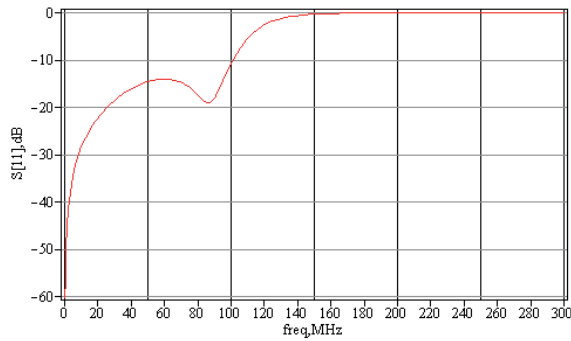
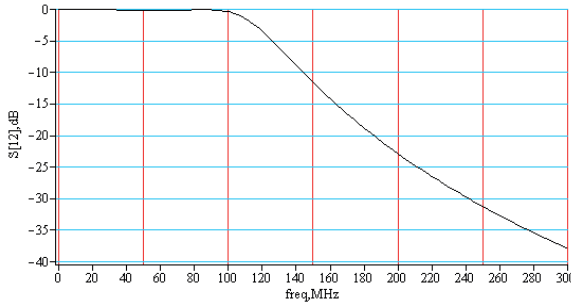
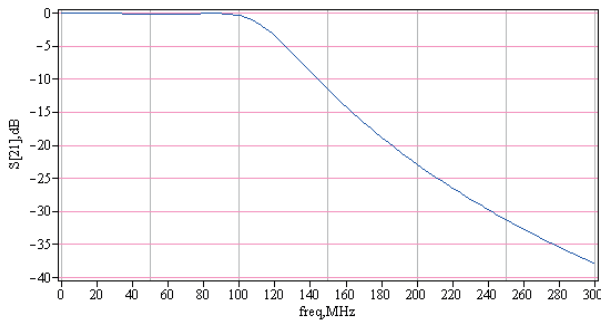
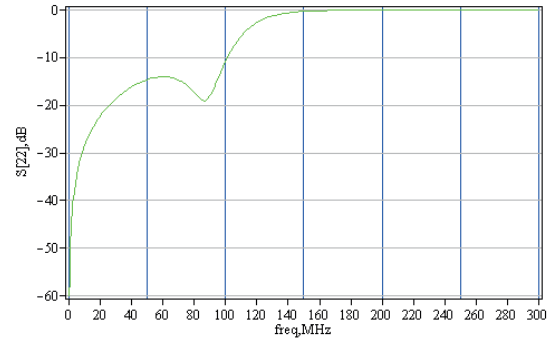


$$S_{11} = \frac{\tau_{c1}\tau_{c2}\tau_{L1}\tau_{L2}p^4 + \tau_{L1}\tau_{c2}(\tau_{c1}-\tau_{L2})p^3 + [\tau_{c1}(\tau_{L2}+\tau_{L1})+\tau_{c2}(\tau_{L2}-\tau_{L1})]p^2 + (\tau_{c1}+\tau_{c2}-\tau_{L1}-\tau_{L2})p}{\tau_{c1}\tau_{c2}\tau_{L1}\tau_{L2}p^4 + \tau_{L1}\tau_{c2}(\tau_{c1}+\tau_{L2})p^3 + (\tau_{c1}+\tau_{c2})(\tau_{L1}+\tau_{L2})p^2 + (\tau_{c1}+\tau_{c2}+\tau_{L1}+\tau_{L2})p+2} \quad (36)$$

$$S_{22} = \frac{-\tau_{c1}\tau_{c2}\tau_{L1}\tau_{L2}p^4 + \tau_{L1}\tau_{c2}(\tau_{c1}-\tau_{L2})p^3 + [\tau_{c1}(\tau_{L2}-\tau_{L1})-\tau_{c2}(\tau_{L2}+\tau_{L1})]p^2 + (\tau_{c1}+\tau_{c2}-\tau_{L1}-\tau_{L2})p}{\tau_{c1}\tau_{c2}\tau_{L1}\tau_{L2}p^4 + \tau_{L1}\tau_{c2}(\tau_{c1}+\tau_{L2})p^3 + (\tau_{c1}+\tau_{c2})(\tau_{L1}+\tau_{L2})p^2 + (\tau_{c1}+\tau_{c2}+\tau_{L1}+\tau_{L2})p+2} \quad (37)$$

$$S_{12} = \frac{2}{\tau_{c1}\tau_{c2}\tau_{L1}\tau_{L2}p^4 + \tau_{L1}\tau_{c2}(\tau_{c1}+\tau_{L2})p^3 + (\tau_{c1}+\tau_{c2})(\tau_{L1}+\tau_{L2})p^2 + (\tau_{c1}+\tau_{c2}+\tau_{L1}+\tau_{L2})p+2} \quad (38)$$

$$S_{21} = \frac{2}{\tau_{c1}\tau_{c2}\tau_{L1}\tau_{L2}p^4 + \tau_{L1}\tau_{c2}(\tau_{c1}+\tau_{L2})p^3 + (\tau_{c1}+\tau_{c2})(\tau_{L1}+\tau_{L2})p^2 + (\tau_{c1}+\tau_{c2}+\tau_{L1}+\tau_{L2})p+2} \quad (39)$$

Figure 10: Reflexion coefficient S_{11} seen at entryFigure 11: Transmission coefficient S_{12} seen from exit to entryFigure 12: Transmission coefficient S_{21} seen from entry to exitFigure 13: Reflexion coefficient S_{22} seen at exit

The purpose of these simulations is to validate this new determination method of scattering parameters from a causal bond graph model of a filter often functioning in high frequency and contrary to the work carried out by Pr A. KAMEL [3] where the causality concept, which represents a significant property in the formalism with network type and in particular the bond graph formalism, was ignored.

All simulation given by figure 10, 11, 12 and 13 were carried out in the MAPLE software. They give us the curves of the reflexion coefficients (S_{11} and S_{22}) and transmission coefficients (S_{12} and S_{21}). These curves give us information about the cut-off frequency and the type of the studied filter which is a low-pass filter with cut-off frequency 100 MHz.

The simulation given by the figure 3 which was carried out in the HP-ADS software and the simulation by the new analytical method given by figure 10, 1, 12 and 13 all show that the two representations are equivalent. Thus we can say that this new method is validated. It gives us always the same results given by the classic techniques of conception and simulation of the microwave circuits.

4. Scattering Bond Graph realization

The scattering matrix [4] of our studied process is 2-2. It is a particular form [18] despite the complexity of expression of the series impedance or parallel admittance [3]. It is orthogonal since the process is considered without loss, is not a transfer matrix and it admits the following general form.

$$S = \begin{bmatrix} b_n^{11}p^n + \dots + b_0^{11} & b_n^{12}p^n + \dots + b_0^{12} \\ b_n^{21}p^n + \dots + b_0^{21} & b_n^{22}p^n + \dots + b_0^{22} \end{bmatrix} \quad (40)$$

$$a_n p^n + a_{n-1} p^{n-1} + \dots + a_0$$

We note that:

$$d(p) = a_n p^n + a_{n-1} p^{n-1} + \dots + a_0 \quad (41)$$



Now, we will use the method which is developed by Pr. A. Kamel.

Indeed, if we consider the scattering matrix form found above for the process alone, we can say that it is not a true transfer matrix [8]. Moreover, it is not in the adequate form since its various S_{ij} parameters and sometimes S_{ij} have the numerator's degree equal to that of denominator and that poses a major problem to determinate the scattering bond graph model of any physical system studied in a general way.

The solution to this problem is to consider the scattering matrix of a process as a transfer matrix connecting the incident and the reflected waves in a symbolic system form.

We start by carrying out an Euclidean division of each term of the numerator matrix (scattering parameters) by the common denominator $d(p)$ which leads to the new shape of the scattering matrix [19] such as:

$$S = S' + D \quad (42)$$

S' : the new scattering matrix with degrees in the numerator at most one less than that of $d(s)$.

D : direct transmission matrix (The rest of the Euclidian division).

$$D = \begin{bmatrix} d_1 & d_3 \\ d_4 & d_2 \end{bmatrix} \quad (43)$$

Thereafter, we seek to apply the alpha-beta method of development in continuous fraction starting from the Routh method [20] and building the corresponding bond graph model, since it is about a multivariable system [18] while being based on the following systematic procedure:

- Calculate the α -Routh table from the common denominator $d(p)$ and the β -Routh table from the new numerator of the S' -matrix.
- Construct the direct chain by using the adequate number of elements I-C (which α_i coefficients are their modules) in integral causality, equal to the degree of $d(p)$.
- Duplicate this chain and construct the two entries of the quadruple.
- Construct the tow outputs by using information bonds and a sufficient number of TF and GY

elements whose modules are precisely the coefficients.

- Add the direct part (transmission matrix D) by using information bonds.
- To obtain the scattering bond graph model of the physical system, it is enough to add the reflexion coefficient $\rho_g = \frac{z_0 - 1}{z_0 + 1}$ of the source and the reflexion coefficient $\rho_c = \frac{z_L - 1}{z_L + 1}$ of the load to the scattering bond graph model of the process to the adequate sites.

It is interesting to notice that the structure of the scattering bond graph of the process remains the same whatever the degree of the common denominator of scattering matrix. The only thing that changes is the corresponding number of I and C linked to the α -Routh expansion [3, 13].

$$S'_{11} = -\frac{2\tau_{c2}\tau_{L1}\tau_{L2}p^3 + 2\tau_{L1}\tau_{c2}p^2 + 2(\tau_{L1} + \tau_{L2})p + 2}{\tau_{c1}\tau_{c2}\tau_{L1}\tau_{L2}p^4 + \tau_{L1}\tau_{c2}(\tau_{c1} + \tau_{L2})p^3 + (\tau_{c1} + \tau_{c2})(\tau_{L1} + \tau_{L2})p^2 + (\tau_{c1} + \tau_{c2} + \tau_{L1} + \tau_{L2})p + 2} \quad (44)$$

$$S'_{12} = \frac{2}{\tau_{c1}\tau_{c2}\tau_{L1}\tau_{L2}p^4 + \tau_{L1}\tau_{c2}(\tau_{c1} + \tau_{L2})p^3 + (\tau_{c1} + \tau_{c2})(\tau_{L1} + \tau_{L2})p^2 + (\tau_{c1} + \tau_{c2} + \tau_{L1} + \tau_{L2})p + 2} \quad (45)$$

$$S'_{21} = \frac{2}{\tau_{c1}\tau_{c2}\tau_{L1}\tau_{L2}p^4 + \tau_{L1}\tau_{c2}(\tau_{c1} + \tau_{L2})p^3 + (\tau_{c1} + \tau_{c2})(\tau_{L1} + \tau_{L2})p^2 + (\tau_{c1} + \tau_{c2} + \tau_{L1} + \tau_{L2})p + 2} \quad (46)$$

$$S'_{22} = \frac{2\tau_{c1}\tau_{c2}\tau_{L1}p^3 + 2\tau_{L1}\tau_{c2}p^2 + 2(\tau_{c1} + \tau_{c2})p + 2}{\tau_{c1}\tau_{c2}\tau_{L1}\tau_{L2}p^4 + \tau_{L1}\tau_{c2}(\tau_{c1} + \tau_{L2})p^3 + (\tau_{c1} + \tau_{c2})(\tau_{L1} + \tau_{L2})p^2 + (\tau_{c1} + \tau_{c2} + \tau_{L1} + \tau_{L2})p + 2} \quad (47)$$

$$D = \begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix} \quad (48)$$

The alpha-beta coefficients are then:

From $d(p)$ we have:

- $\alpha_1, \alpha_2, \alpha_3$ and α_4 .

From S'_{11} we have:

- $\beta_1^{11}, \beta_2^{11}, \beta_3^{11}$ and β_4^{11}

From $S'_{12} = S'_{21}$ we have:

- $\beta_1^{12} = \beta_1^{21}, \beta_2^{12} = \beta_2^{21}, \beta_3^{12} = \beta_3^{21}$ and $\beta_4^{12} = \beta_4^{21}$

From S'_{22} we have:

- $\beta_1^{22}, \beta_2^{22}, \beta_3^{22}$ and β_4^{22}



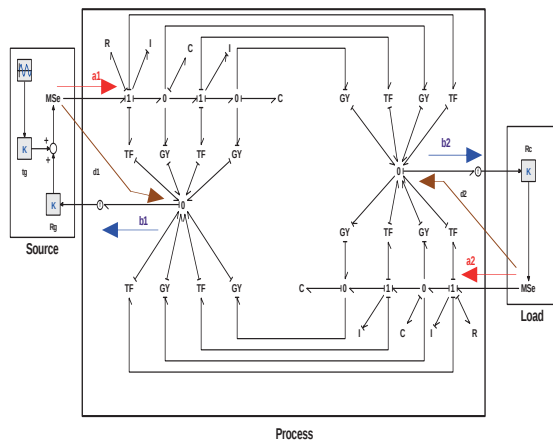


Figure 14: Scattering bond graph model of the low-pass filter connecting to its source and load

5. Conclusion

In this study, we showed how we can find the scattering parameters (scattering matrix S) of Tchebychev low-pass filter functioning in high frequency by a jointly use of the scattering formalism and the bond graph technique and by taking into account the causality concept.

Indeed, by adopting the reticulation assumption which allows the phenomena separation and the orthogonality property of the scattering matrix S associated to a physical system, we showed the existence of an ideal structure junction of Kirchhoff which includes a junction with common effort and flow known as a decomposition junction (0-junction or 1-junction: according to the studied filter type).

The new determination method which applied to a filter functioning in high frequency, makes it possible, on the one hand, to obtain a scattering representation of complex systems and on the other hand to confirm that the scattering formalism has the same properties as the bond graph formalism and thus belonged to the formalism's class of network type.

Finally, by applying the procedure described previously, we build the famous bond graph model often named: Scattering Bond Graph which will enable us to capture the power transfers in a simple and direct manner at the same time. It provides us with a temporal approach of the phenomena usually modeled with the frequencies tools.

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7. Biography



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Minimum Switching Loss PWM Algorithms for Three-Phase Voltage Source Inverter Fed Induction Motor Drives

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Abstract

This paper presents a detailed analysis of the switching loss characteristics of various existing discontinuous PWM (DPWM) algorithms, which use only one zero state and advanced DPWM (ADPWM) algorithms which use only one zero state with active state division. These DPWM algorithms reduce the switching losses at any operating conditions when compared with conventional space vector PWM (CSVPWM). Moreover, to reduce the complexity involved in the conventional space vector approach, the proposed PWM algorithms are developed by using the concept of imaginary switching times. By analyzing the switching loss characteristics, the minimum switching loss PWM algorithms are developed for induction motor drives. The theoretical evaluation is validated through the numerical simulation studies.

Keywords: ADPWM, DPWM, MSLPWM, space vector PWM, switching loss characteristics.

1. Nomenclature

f_s	Sampling frequency
f_{sw}	Average switching frequency
E_{sub}	Average switching energy loss per subcycle
V_{dc}	DC link voltage
n_a	Number of switchings per sampling time period in phase A
P_{sw}	Normalized switching loss
ϕ	Power factor angle
δ	Phase-angle

2. Introduction

The variable speed induction motor drives require variable voltage, variable frequency voltages, which can be obtained by using the voltage source inverters (VSI). Hence, nowadays the PWM algorithms for VSI are becoming popular. A detailed survey on PWM algorithms is given in [1]. Among the various PWM algorithms the CSVPWM algorithm is popular due to its numerous advantages compared with the sinusoidal PWM [2]. By utilizing the division of zero state time, several DPWM algorithms can be generated and a detailed study about this is given in [3]. Recently, novel PWM algorithms have been developed which use only one zero state same as existing DPWM algorithms, but involve the division of active state time in every sampling time interval. These ADPWM algorithms can be generated with space vector approach very easily when compared with the triangle comparison approach [4]. A detailed analysis of these ADPWM algorithms has been given in [5]. But, in the recent years, the research is focussed on the analysis of the switching loss of the inverter. Several authors have proposed various methods for reduced switching loss of the inverter [6]-[9]. However, the above papers deal with the conventional space vector approach, which involves the calculation of angle and sector information. Hence, the complexity involved in the conventional space vector approach is more. To overcome this problem, few PWM algorithms have been developed in [10] by using the concept of imaginary switching times.

This paper presents different PWM algorithm using the concept of imaginary switching times. The



Proposed algorithm reduces the switching losses of the inverter. Also this presets the minimum switching loss PWM algorithms for induction motor drives.

Section 3 gives the details about the generation of various PWM algorithms. A detailed analysis on switching loss characteristics is given in section 4 for various PWM algorithms. Moreover, the minimum switching loss PWM algorithms are given in this section.

3. Switching Sequences

The proposed approach uses the instantaneous reference phase voltages only to calculate switching times. This method does not depend on the magnitude of the reference voltage space vector and its relative angle with respect to the reference axis. If the reference voltage vector lies in the first sector, then the actual switching times can be deduced as follows [10]:

$$T_1 = \frac{T_s}{V_{dc}} V_{an} - \frac{T_s}{V_{dc}} V_{bn} \equiv T_{an} - T_{bn} \quad (1)$$

$$\text{And } T_2 = \frac{T_s}{V_{dc}} V_{bn} - \frac{T_s}{V_{dc}} V_{cn} \equiv T_{bn} - T_{cn} \quad (2)$$

From the above expressions, the imaginary switching time periods proportional to the instantaneous values of the reference phase voltages are defined as

$$\begin{aligned} T_{an} &\equiv \left(\frac{T_s}{V_{dc}} \right) V_{an} \\ T_{bn} &\equiv \left(\frac{T_s}{V_{dc}} \right) V_{bn} \\ T_{cn} &\equiv \left(\frac{T_s}{V_{dc}} \right) V_{cn} \end{aligned} \quad (3)$$

Thus, the active voltage vector switching times can be represented by the time difference between the imaginary switching time periods. The switching times T_{an} , T_{bn} and T_{cn} could be negative when the instantaneous reference voltages are negative. Hence, these times are called as imaginary switching times. The active vector switching times can be calculated in each sampling interval as follows:

$$\begin{aligned} T_{Max} &= \text{Max}(T_{an}, T_{bn}, T_{cn}) \\ \text{Let } T_{Min} &= \text{Min}(T_{an}, T_{bn}, T_{cn}) \\ T_{Mid} &= \text{Mid}(T_{an}, T_{bn}, T_{cn}) \end{aligned} \quad (4)$$

where Max, Min and Mid are the nominal values used during the sampling interval. The function $\text{Max}(T_{an}, T_{bn}, T_{cn})$ selects the maximum value among T_{an} , T_{bn} and T_{cn} . Similarly

$\text{Min}(T_{an}, T_{bn}, T_{cn})$ selects the minimum value and $\text{Mid}(T_{an}, T_{bn}, T_{cn})$ selects the middle value. Finally, the active state times T_1 and T_2 may be expressed as [10]

$$\begin{aligned} T_1 &= T_{Max} - T_{Mid} \\ T_2 &= T_{Mid} - T_{Min} \end{aligned} \quad (5)$$

The zero voltage vectors switching time is calculated using (6).

$$T_z = T_s - T_1 - T_2 \quad (6)$$

The CSVPWM algorithm employs equal division of zero voltage vector time within a sampling time period. However, by utilizing the freedom of zero state time division, various discontinuous PWM (DPWM) algorithms can be generated. In the proposed PWM sequences the zero state time will be shared between two zero states as T_0 for V_0 and T_7 for V_7 respectively, and can be expressed as [6]

$$T_0 = k_o T_z; T_7 = (1 - k_o) T_z \quad (7)$$

If $k_o = 0.5, 0$ and 1 , then CSVPWM, DPWMMAX and DPWMMIN can be obtained respectively. When $k_o = 0$, any one of the phases is clamped to positive dc bus for 120 degrees over a fundamental interval and when $k_o = 1$, any one of the phases is clamped to negative dc bus for 120 degrees over a fundamental interval. Thus, in the first sector, CSVPWM uses 0127-7210 sequence, DPWMMAX uses 721-127 sequence and DPWMMIN uses 012-210 sequence. Various DPWM algorithms can be generated with step change of k_o between zero and one [3].

The above existing DPWM algorithms cannot switch more than once in every sampling time period. Hence, these can be generated with triangular comparison approach also. But in the proposed switching sequences, one of the phases will be clamped while the one of the other phases will switches twice in every sampling time interval. Hence these sequences also known as double-switching clamping sequences. Same as the existing DPWM algorithms, by changing k_o value and using the active state division, advanced DPWM algorithms can be generated. If $k_o = 0$ and 1 , then ADPWMMAX and ADPWMMIN can be obtained respectively. The switching sequences pertaining to all six sectors for these PWM algorithms are listed in Table 1. Moreover, the Table 1 shows the clamping phase and double-switching phase also in every sector for ADPWMMIN and ADPWMMAX algorithms. The other ADPWM algorithms can be generated with step change of k_o between zero and one as given in [3]. The following Tables will



give the comparison between the existing DPWM and ADPWM algorithms. After examining the all possible advanced DPWM (ADPWM) algorithms, it can be observed that in each ADPWM algorithm though one of the phases switches twice in a sampling time interval the total number of commutations per subcycle is only three. This is same as the CSVPWM algorithm. Hence the sampling frequency of the CSVPWM and ADPWM algorithms is the twice the average switching frequency ($f_s = 2f_{sw}$), whereas the sampling frequency of the existing DPWM algorithms is three times the average switching frequency ($f_s = 3f_{sw}$).

4. Switching Loss Characteristics

The switching losses of a pulse width modulated VSI fed induction motor drive are load dependent and increase with the current magnitude. The switching losses of the inverter also depend on type of PWM method. With continuous PWM methods, all the three phase currents are commutated within each carrier cycle of a full fundamental cycle. Therefore, for all continuous PWM methods the switching losses are the same and independent of the load power factor angle. However, with the DPWM methods, the switching losses are significantly influenced by the type of modulation method and load power factor angle.

Table 1: ADPWMMAX and ADPWMMIN sequences in all six sectors

Sector	ADPWMMIN			ADPWMMAX		
	sequence	Clamping phase	Double Switching phase	sequence	Clamping phase	Double Switching phase
I	0121-1210	c	b	7212-2127	a	b
II	0323-3230	c	a	7232-2327	b	a
III	0343-3430	a	c	7434-4347	b	c
IV	0545-5450	a	b	7454-4547	c	b
V	0565-5650	b	a	7656-6567	c	a
VI	0161-1610	b	c	7616-6167	a	c

Table2:Switching sequences for DPWM0 and ADPWM0

Sector	DPWM0	ADPWM0
I	012-210	0121-1210
II	723-327	7232-2327
III	034-430	0343-3430
IV	745-547	7454-4547
V	056-650	0565-5650
VI	761-167	7616-6167

Table3:Switching sequences for DPWM2 and ADPWM2

Sector	DPWM2	ADPWM2
I	721-127	7212-2127
II	032-230	0323-3230
III	743-347	7434-4347
IV	054-450	0545-5450
V	765-567	7656-6567
VI	016-610	0161-1610

Table 4: Switching sequences for DPWM1 and ADPWM1:

Sector	DPWM1		ADPWM1	
	$0 \leq \alpha \leq 30^\circ$	$30^\circ \leq \alpha \leq 60^\circ$	$0 \leq \alpha \leq 30^\circ$	$30^\circ \leq \alpha \leq 60^\circ$
I	721-127	012-210	7212-2127	0121-1210
II	032-230	723-327	0323-3230	7232-2327
III	743-347	034-430	7434-4347	0343-3430
IV	054-450	745-547	0545-5450	7454-4547
V	765-567	056-650	7656-6567	0565-5650
VI	016-610	761-167	0161-1610	7616-6167



Table 5: Switching sequences for DPWM3 and ADPWM3:

Sector	DPWM3		ADPWM3	
	$0 \leq \alpha \leq 30^\circ$	$30^\circ \leq \alpha \leq 60^\circ$	$0 \leq \alpha \leq 30^\circ$	$30^\circ \leq \alpha \leq 60^\circ$
I	012-210	721-127	0121-1210	7212-2127
II	723-327	032-230	7232-2327	0323-3230
III	034-430	743-347	0343-3430	7434-4347
IV	745-547	054-450	7454-4547	0545-5450
V	056-650	765-567	0565-5650	7656-6567
VI	761-167	016-610	7616-6167	0161-1610

In the DPWM methods, the devices are clamped to either negative bus or positive bus for a total of 120° and hence reduce the switching losses of inverter over continuous PWM methods. Hence, in DPWM algorithms, the load power factor and the modulation method together determine the time interval that the load current is not commutated. Therefore, it is necessary to derive the switching loss characteristics to compare the switching losses of various DPWM algorithms. This section presents a comparison of inverter switching losses due to conventional SVPWM and DPWM methods.

The switching loss in an IGBT depends mainly on the dc link voltage (V_{dc}) instantaneous line current and turn-on and turnoff times. However, the V_{dc} and times are assumed to be constant for different instantaneous line currents. Hence, to study the switching losses of the inverter, it is sufficient to consider the product of instantaneous line current magnitude of a particular phase and the number of switchings per sampling time period in that phase (n_a), corresponding to the PWM sequence considered. This product is referred to as the switching loss factor (SLF). Since the three phases are symmetric, it is enough to analyze one phase only. The switching losses of a PWM-VSI induction motor drive can be modeled analytically by assuming linear current turn-on and turn-off characteristics with respect to time for the inverter switching devices and considering only fundamental component of the load current. Let the phase current is

$$i_a = I_{\max} \sin(\omega t - \phi) \quad (8)$$

where i_a is the instantaneous fundamental phase current, $I_{\max}$ is the maximum value of the fundamental phase current and ϕ is the line side power factor angle. The average switching energy

loss per subcycle (E_{sub}) in an inverter leg is as given by

$$E_{sub}(avg) = \frac{1}{\pi} \int_0^\pi \frac{n_a |I_{\max} \sin(\omega t - \phi)|}{I_{\max}} d(\omega t) \quad (9)$$

$$= \frac{1}{\pi} \int_0^\pi n_a |\sin(\omega t - \phi)| d(\omega t)$$

To obtain the measure of the inverter switching losses, the average switching energy loss per subcycle must be multiplied by the number of subcycles per second, i.e., the sampling frequency (f_s). The sampling frequency of the CSVPWM and ADPWM algorithms is two times the switching frequency (f_{sw}), while it is three times the switching frequency (f_{sw}) for the existing DPWM methods. The average switching energy loss over a fundamental cycle for CSVPWM equals $(2/\pi)$. The normalized switching loss due to given PWM algorithm can be obtained as given in (10).

$$P_{sw} = \frac{E_{sub}(avg)}{(2/\pi)} * \frac{f_s}{2f_{sw}} \quad (10)$$

From (10), the normalized switching loss due to existing DPWM methods can be obtained and given in (11).

$$P_{sw} = \frac{3\pi}{4} E_{sub}(avg) \quad (11)$$

By observing the DPWM0, DPWM1 and DPWM2 modulating waveforms, it can be given that there is a 30° phase-angle (δ) distance between their dc-link clamped 60° segments. Hence, a new PWM algorithm can be introduced as generalized DPWM (GDPWM) algorithm which covers the DPWM0, DPWM1 and DPWM2 algorithms. The δ and ϕ dependent switching phase current and normalized switching energy loss per subcycle waveforms of GDPWM algorithm is shown in Fig.1. The GDPWM



algorithm can be represented by using space vector as shown in Figure 2. For $\delta = 0^\circ$, 30° and 60° , DPWM0, DPWM1 and DPWM2 algorithms can be obtained respectively. The variation of average switching energy loss per subcycle (E_{sub}) over a fundamental cycle for various DPWM algorithms for different values of δ and ϕ is shown in Figure 3- Figure 6. From these, it can be observed that at unity power factor DPWM1 clamps a phase around its current peak, which leads to a significant reduction in $E_{sub}(avg)$ over the remaining DPWM and conventional SVPWM algorithms. Therefore, the switching loss mainly depends on the power factor angle by which the line current lags/leads the line voltage. Moreover, it may be observed that the effect of different PWM sequences on the switching loss does not depend on V_{ref} or the fundamental frequency.

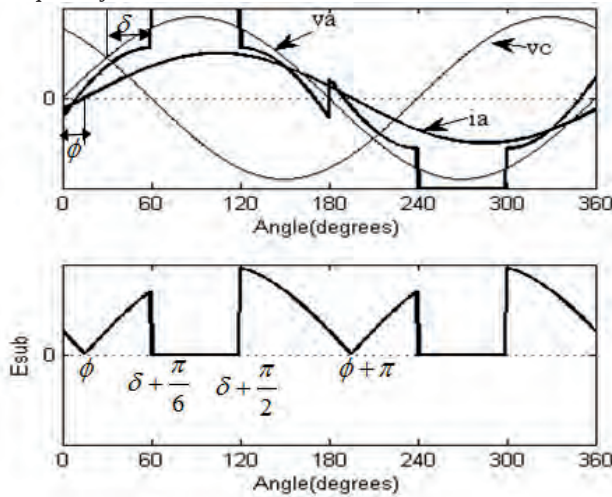


Figure 1: the average switching loss of GDPWM

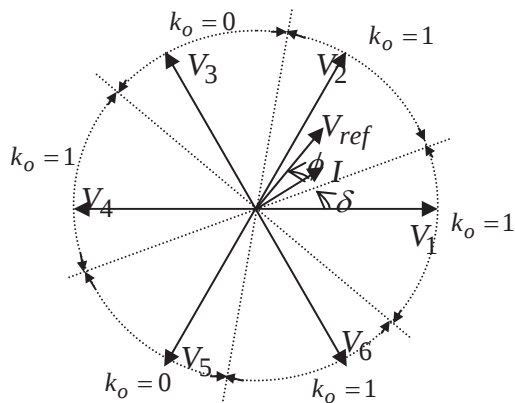


Figure 2: space vector illustration of GDPWM algorithm

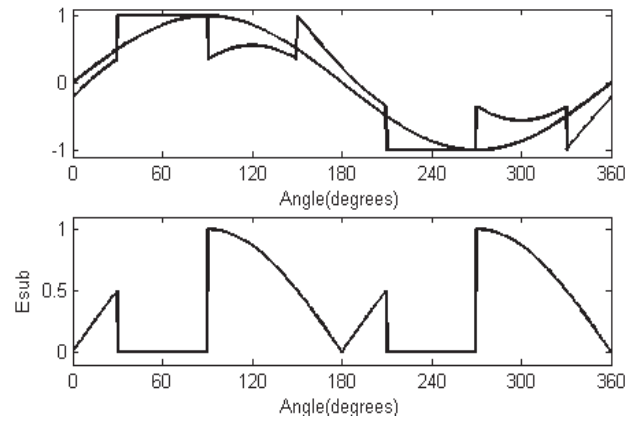


Figure 3(a)

From Figure 3 – Figure 6, the expressions for normalized inverter switching loss corresponding to different DPWM algorithms can be derived as given in [3]. The variation of normalized switching loss of different DPWM algorithms with power factor angle (both at lagging and leading) is shown in Figure 7.

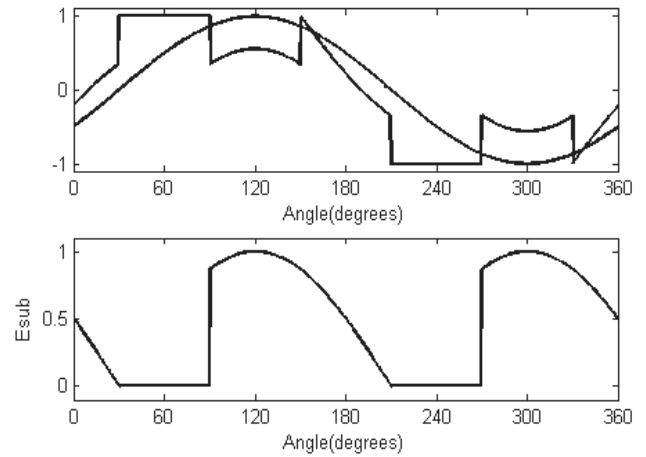


Figure 3(b)

Figure 3. Variation of normalized switching energy loss for DPWM0 method: (a) $\phi = 0^\circ$ (b) $\phi = 30^\circ$

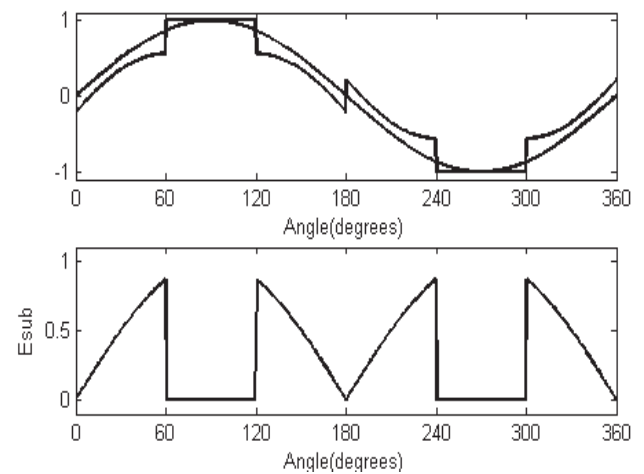


Figure 4(a)



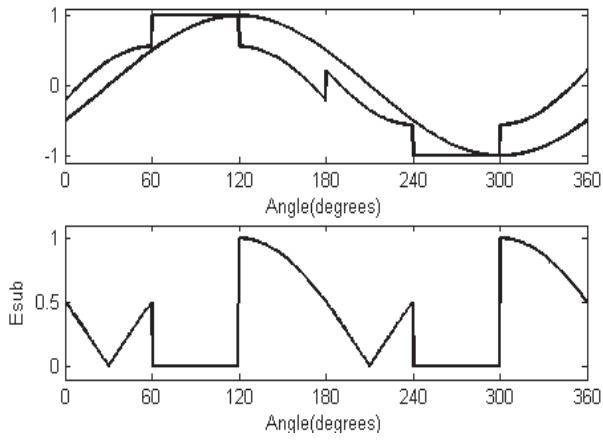


Figure 4: Variation of normalized switching energy loss for DPWM1 method: (a) $\phi = 0^\circ$ (b) $\phi = 30^\circ$

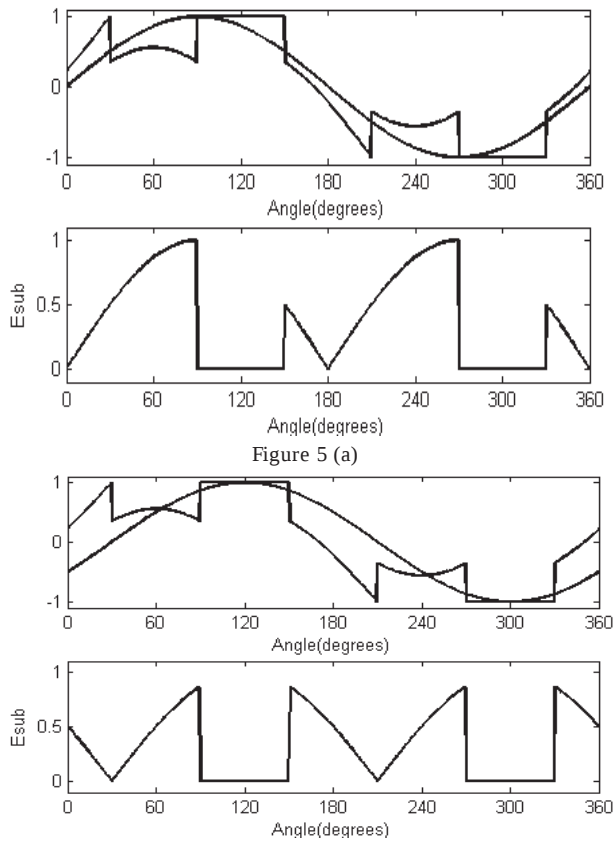


Figure 5: Variation of normalized switching energy loss for DPWM2 method: (a) $\phi = 0^\circ$ (b) $\phi = 30^\circ$

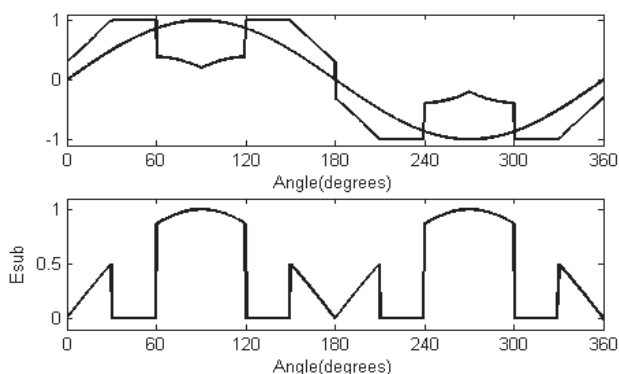


Figure 6 (a)

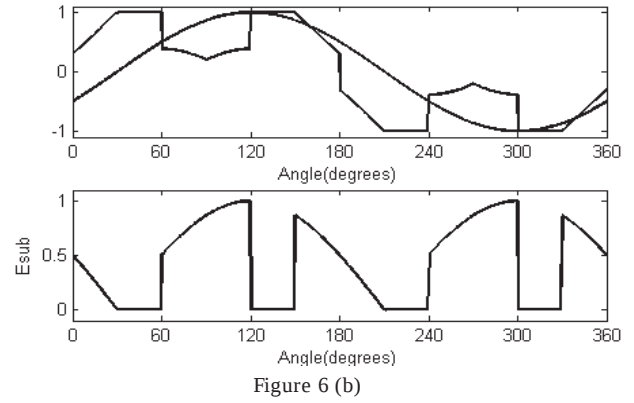


Figure 6: Variation of normalized switching energy loss for DPWM3 method: (a) $\phi = 0^\circ$ (b) $\phi = 30^\circ$

From Fig.7, it can be found that the DPWM1 gives minimum switching loss at unity power factor, because DPWM1 clamps at peak phase current at unity power factor. Similarly, DPWM0 and DPWM2 give minimum switching losses at 30° leading and lagging power factors respectively. But, DPWM3 gives minimum switching loss near the zero power factor. The value of δ can be varied in accordance with ϕ to achieve reduction in switching losses.

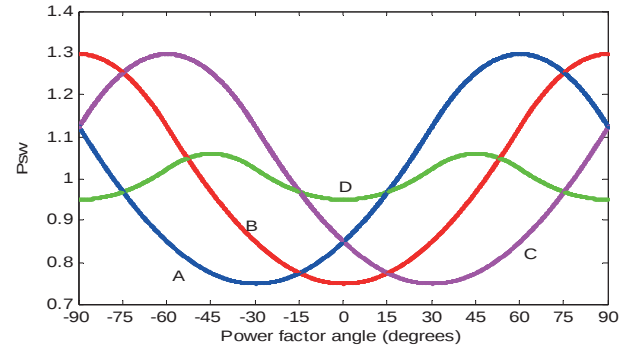


Figure 7 The variation of normalized switching loss of different DPWM algorithms (A: DPWM0; B: DPWM1; C: DPWM2 and D: DPWM3)

The minimum switching power loss solution of the DPWM0, DPWM1 and DPWM2 yields to GDPWM algorithm. The optimal solution of GDPWM is obtained by selecting $\delta = (\pi/6) + \phi$ for $-(\pi/6) \leq \delta \leq (\pi/6)$. Outside this range $\delta = 60^\circ$ for lagging power factor angle and $\delta = 0^\circ$ for leading power factor angle. The normalized switching loss variations for different DPWM algorithms and GDPWM algorithm are shown in Fig. 8. This shows that the GDPWM algorithm combines the DPWM0 and DPWM1 and DPWM2 algorithms and also gives less switching loss. The GDPWM does not consist of DPWM3 algorithm. But from Fig.7, it can be observed that the DPWM3 gives minimum switching losses outside the $-(5\pi/12) \leq \phi \leq (5\pi/12)$ range. In this paper, by considering DPWM3, the minimum switching loss PWM (MSLPWM) algorithm with



existing DPWM algorithms is proposed. The variations of normalized switching losses of various DPWM algorithms and proposed minimum switching loss PWM (MSLPWM) algorithm are shown in Figure 9. The comparison between GDPWM and proposed MSLPWM is shown in Figure 10.

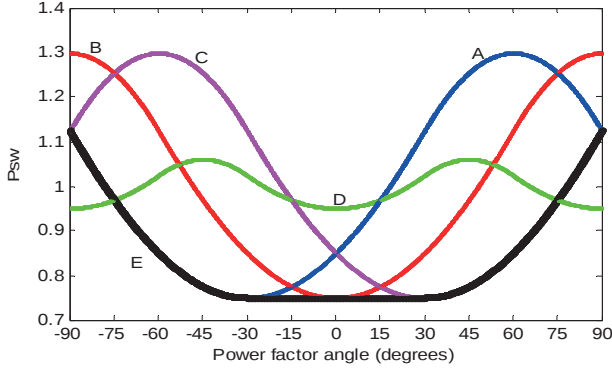


Figure 8: The variation of normalized switching loss of different DPWM algorithms with power factor angle (A: DPWM0; B: DPWM1; C: DPWM2; D: DPWM3 and E=GDPWM)

Similar to the existing DPWM algorithms, the switching loss analysis of ADPWM algorithms can be carried out. The normalized switching loss due to ADPWM algorithm can be obtained same as previous chapter and given by

$$P_{sw,ADPWM} = \frac{\pi}{2} E_{sub}(avg) \quad (12)$$

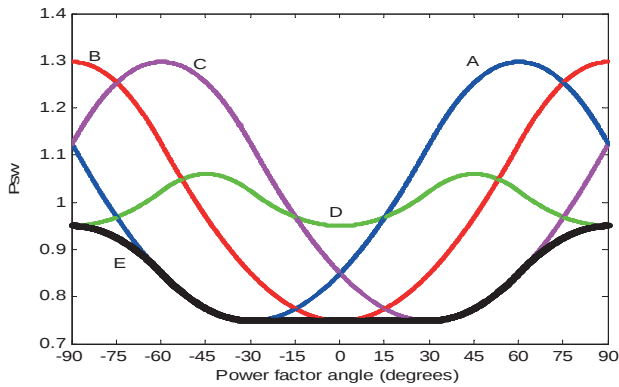


Figure 9: The variation of normalized switching loss of different DPWM algorithms with power factor angle (A: DPWM0; B: DPWM1; C: DPWM2; D: DPWM3 and E= MSLPWM)

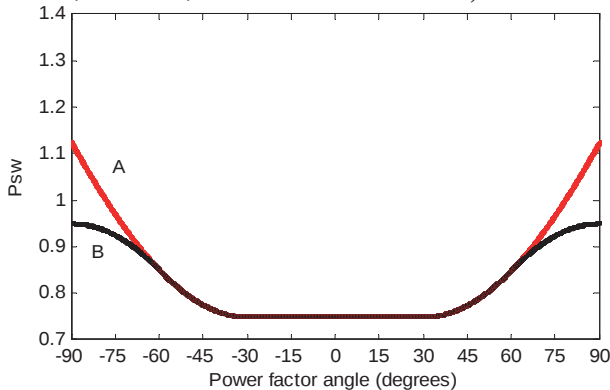


Figure 10: The variation of normalized switching loss of GDPWM (A) and MSLPWM (B) algorithms

The modulating waveforms of ADPWM0, ADPWM1, ADPWM2 and ADPWM3 are similar to corresponding existing DPWM algorithms. Hence, same as existing DPWM0, DPWM1 and DPWM2 algorithms, there is a 30° phase-angle (δ) distance between their dc-link clamped 60° segments in the ADPWM0, ADPWM1 and ADPWM2 modulating waveforms also. Hence, a new PWM algorithm can be introduced as advanced generalized DPWM (AGDPWM) algorithm which covers the ADPWM0, ADPWM1 and ADPWM2 algorithms. The variation of average switching energy loss per subcycle (E_{sub}) over a fundamental cycle for various ADPWM algorithms for different values of δ and ϕ is shown in Figure 11 - Figure 14.

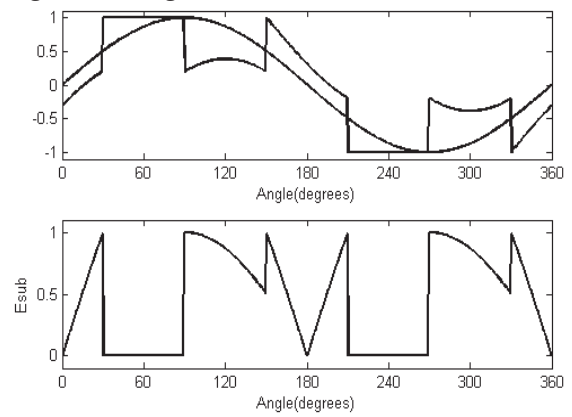


Figure 11 (a)

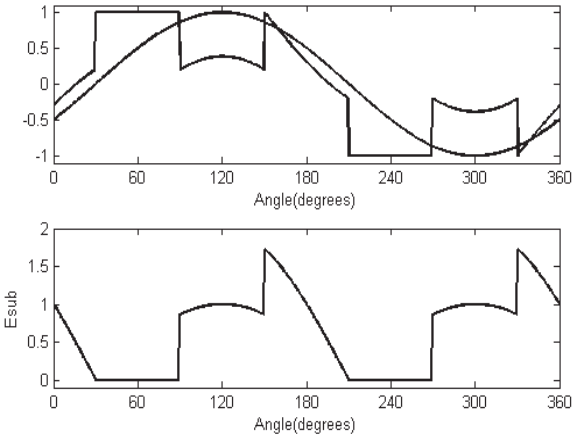


Figure 11 (b)

Figure 11: Variation of normalized switching energy loss for ADPWM0 method: (a) $\phi = 0^\circ$ (b) $\phi = 30^\circ$

At the same time ADPWM3 is not effective in reducing the switching energy loss at unity power factor. At zero power factor lagging, ADPWM3 reduces the $E_{sub}(avg)$. Thus, both in existing as well as advanced DPWM algorithms, DPWM1 and ADPWM1 are better in terms of switching losses at power factors close to unity, while DPWM3 and ADPWM3 are better at power factors close to zero. From Figure 11 – Figure 14, the expressions for



normalized inverter switching loss corresponding to different ADPWM algorithms can be derived as given in [8]. The variation of normalized switching loss of different ADPWM algorithms with power factor angle (both at lagging and leading) is shown in Figure 15.

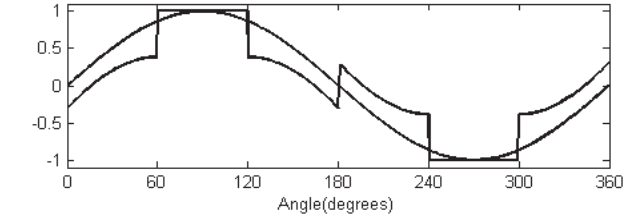


Figure 12 (a)

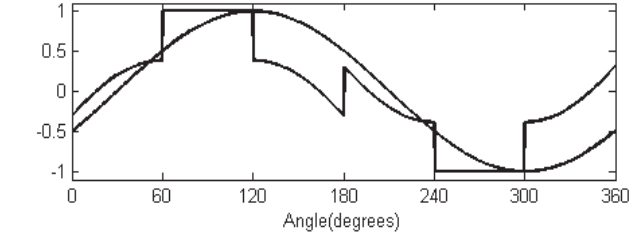


Figure 12 (b)

Figure 12: Variation of normalized switching energy loss for ADPWM1 method: (a) $\phi = 0^\circ$ (b) $\phi = 30^\circ$

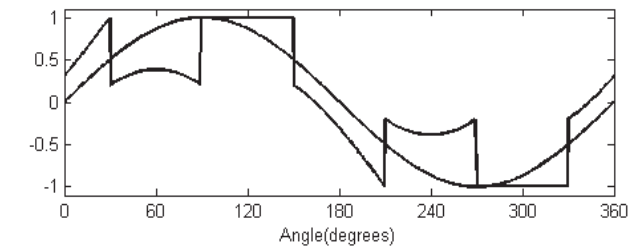


Figure 13 (a)

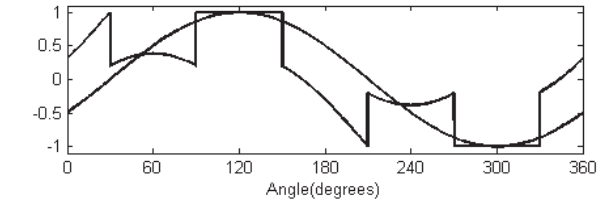
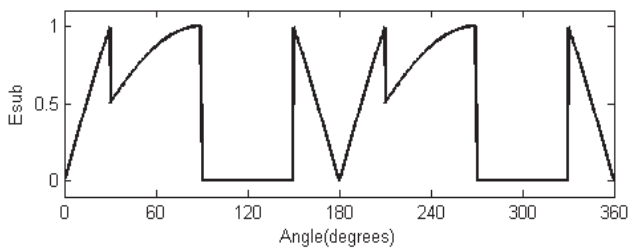


Figure 13 (b)

Figure 13: Variation of normalized switching energy loss for ADPWM2 method: (a) $\phi = 0^\circ$ (b) $\phi = 30^\circ$

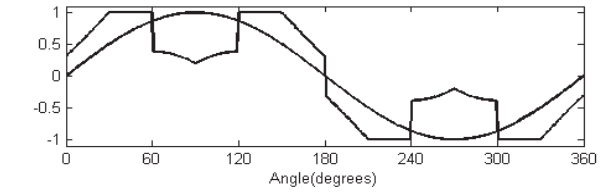


Figure 14 (a)

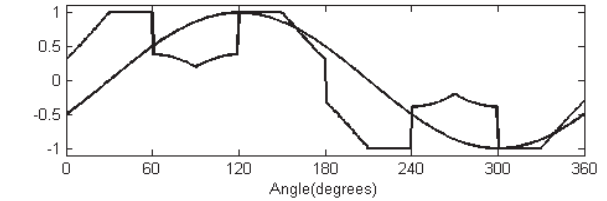


Figure 14 (b)

Figure 14: Variation of normalized switching energy loss for ADPWM3 method: (a) $\phi = 0^\circ$ (b) $\phi = 30^\circ$

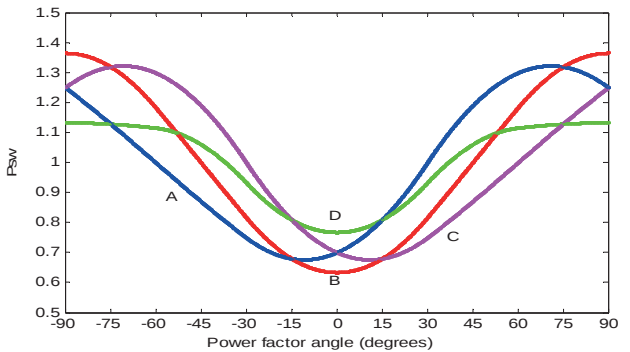


Figure 15: The variation of normalized switching loss of different ADPWM algorithms with power factor angle (A: ADPWM0; B: ADPWM1; C: ADPWM2 and D: ADPWM3)



From Figure 15, it can be observed that the ADPWM1 gives minimum switching loss at unity power factor, because ADPWM1 clamps at peak phase current at unity power factor. Similarly, ADPWM0 and ADPWM2 give minimum switching losses at 30° leading and lagging power factors respectively. But, ADPWM3 gives minimum switching loss near the zero power factors. The value of δ can be varied in accordance with ϕ to achieve reduction in switching losses. The minimum switching power loss solution of the ADPWM0, ADPWM1 and ADPWM2 yields to AGDPWM algorithm. The optimal solution of AGDPWM is obtained by selecting $\delta = (\pi/6) + \phi$ for $-(\pi/6) \leq \delta \leq (\pi/6)$. Outside this range $\delta = 60^\circ$ for lagging power factor angle and $\delta = 0^\circ$ for leading power factor angle. The normalized switching loss variations for different ADPWM algorithms and AGDPWM algorithm are shown in Fig. 16. This shows that the AGDPWM algorithm combines the ADPWM0 and ADPWM1 and ADPWM2 algorithms and also gives less switching loss.

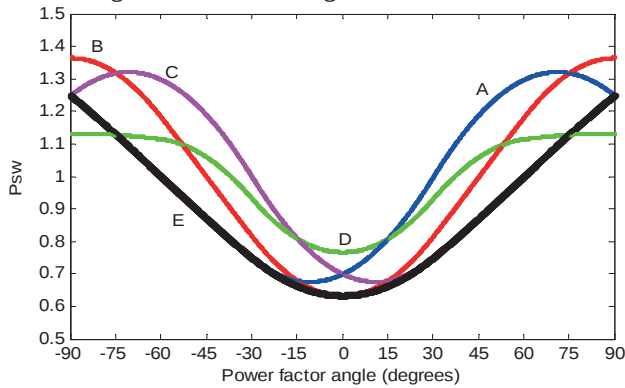


Figure 16: Variation of normalized switching loss of different ADPWM algorithms with power factor angle (A: ADPWM0; B: ADPWM1; C: ADPWM2; D: ADPWM3 and E: AGDPWM)

The AGDPWM does not consist of ADPWM3 algorithm. But from Fig.15, it can be observed that the ADPWM3 gives minimum switching losses outside the $-(5\pi/12) \leq \phi \leq (5\pi/12)$ range. In this paper, by considering ADPWM3 also into account advanced minimum switching loss PWM (AMSLPWM) algorithm with ADPWM algorithms is proposed. The variations of normalized switching losses of various ADPWM algorithms and proposed AMSLPWM algorithm are shown in Fig. 17. The comparison between AMSLPWM and MSLPWM is shown in Fig. 18. From Fig 18, it can be observed that the proposed AMSLPWM algorithm gives minimum switching loss over the MSLPWM in the $-(\pi/6) \leq \phi \leq (\pi/6)$ range. At the same time, MSLPWM algorithm gives minimum switching losses outside the $-(\pi/6) \leq \phi \leq (\pi/6)$ range.

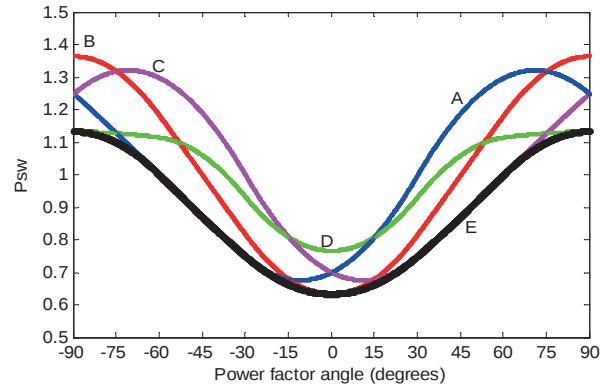


Figure 17: variation of normalized switching loss of different ADPWM algorithms with power factor angle (A: ADPWM0; B: ADPWM1; C: ADPWM2; D: ADPWM3 and E: AMSLPWM)

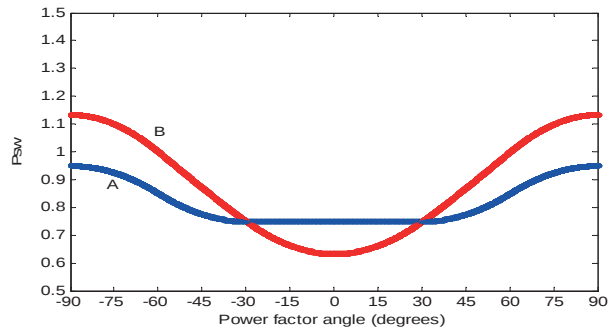


Figure 18: The variation of normalized switching loss of MSLPWM (A) and AMSLPWM (B) algorithms

5. Conclusions

Space vector based minimum switching loss PWM algorithms are presented in this paper. The proposed algorithms did not use the information regarding sector and angle calculation of switching times and hence reduces the complexity involved. The minimum switching loss PWM algorithms are derived using existing DPWM and ADPWM algorithms and compared. From the results, it can be observed that AMSLPWM algorithm gives minimum switching loss over the MSLPWM in the $-(\pi/6) \leq \phi \leq (\pi/6)$ range. At the same time, MSLPWM algorithm gives minimum switching losses outside the $-(\pi/6) \leq \phi \leq (\pi/6)$ range.

6. References

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Adaptive Fuzzy Control combined the Orthogonal Hermite Basis and Sliding Mode approach for Unknown Nonlinear Systems

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Abstract

In this paper, we present an adaptive fuzzy control for a class of unknown nonlinear systems. The strategy of control uses the adaptive fuzzy system Takagi-Sugeno (T-S) to approximate the part of the primary control. In order to guarantee the stability and high performance, the auxiliary part is incorporated in the control law. The proposed compensation control is combined a Hermite function and sliding mode control (SMC). The Hermite function is used to predict and to remove the fuzzy approximation and attenuates the influence of the external disturbances. However, the SMC is designed to ensure the stability and a good tracking. The parameters of the control are adjusted on line by the adaptive law with stability and convergence analysis using the Lyapunov approach. The robust and the stability of the control scheme are proved and simulation results are given to verify the effectiveness of the proposed approach.

Keywords: Adaptive control, Hermite function, Sliding mode, Fuzzy logic, Nonlinear system

1. Introduction

The control of nonlinear systems has been an important research topic [1, 2]. Traditionally, control system design has been tackled using mathematical models derived from physical laws. In fact, most of the parameters and structure of the system are unknown due to environment changes, modelling error and unmodelled dynamics. Then, the designer is confronted with the above problems when

designing control systems. Face the above problems; there exist several techniques, in particular, the intelligent technologies as neural networks, fuzzy logic, genetics algorithms and evolutive computation [3, 9, 10].

Fuzzy logic, as one of the most useful approaches for utilizing expert knowledge, has been an active field of research during the past decade [9, 11]. Fuzzy logic control has found promising applications for a wide variety of industrial systems specifically applicable to plants that are mathematically poorly modelled [7, 16].

The ability of converting linguistic descriptions into automatic control strategy makes it a practical and promising alternative to the classical control scheme for achieving control of complex nonlinear systems. Recently, a great amount of the effort has been devoted to describing nonlinear system using a T-S fuzzy model. Based on the universal approximation capability, many effective adaptive fuzzy control schemes have been developed to incorporate with human expert knowledge information in a systematic way, which can also guarantee stability and performance criteria [3, 4, 10].

There have been many successful applications in fuzzy control in recent years. In spite of the success, there are still many basic issues that remain to be further addressed. Stability analysis and systematic design are certainly among the most important issues for fuzzy control systems [14]. In this respect, several direct and indirect adaptive fuzzy control schemes have been introduced for controlling nonlinear systems [15]. In the direct scheme, the



fuzzy system is used to approximate an unknown ideal controller. On the other hand, the indirect scheme uses fuzzy systems to estimate the plant dynamics and then synthesizes a control law based on these estimates. In these adaptive fuzzy control schemes, the controllers are generally composed of two main components.

This paper proposes an adaptive fuzzy control for nonlinear system with unknown dynamics. The strategy of control is based on fuzzy system combined Hermite function and SMC. The primary control action is approximated by the adaptive fuzzy model type T-S. The auxiliary part of control is incorporated to ensure the stability and the tracking performance. The design of this compensation control is based on Hermite function and SMC. The fuzzy approximation error and the influence of the external disturbances are predicted by using the orthogonal Hermite basis function. The SMC is designed to guarantee the stability and robustness of the proposed approach. The fuzzy and Hermite basis parameters are estimated on line by the adaptive laws with stability and convergence are analysed in the Lyapunov sense.

The paper is organized as follows: the problem formulation is presented in section 2. In section 3, the adaptive fuzzy control is proposed. Simulation results are presented in section 4.

2. Problem Formulation

Consider a nonlinear system described as follows:

$$\begin{cases} \dot{x}_1 = x_2 \\ \dot{x}_2 = x_3 \\ \vdots \\ \dot{x}_n = f(\underline{x}, t) + b u + d(t) \\ y = x_1 \end{cases} \quad (1)$$

Or equivalent:

$$\begin{cases} \dot{x}^{(n)} = f(\underline{x}, t) + b u + d(t) \\ y = x \end{cases} \quad (2)$$

where $\underline{x} = [x, \dot{x}, \dots, x^{(n-1)}]^T = [x_1, x_2, \dots, x_n]^T \in R^n$ is the state vector of the systems which is assumed measurable. The function f is unknown and nonlinear, and b is constant positive. $u \in R$ and $y \in R$ are respectively the input and output system. $d(t)$ is the unknown external disturbance. Our objective is to design an adaptive control which will cause the output y to track a desired reference y_r (i.e., $e_0 \rightarrow 0$) and have up to $(n-1)$ bounded derivatives.

The tracking error defined by:

$$e_0 = y - y_r \quad (3)$$

The control law is designed to have the following idealized control [3]:

$$u^* = \frac{1}{b} (-f(\underline{x}, t) + y_r^{(n)} - \sum_{i=1}^{n-1} k_i e^{(i)}) \quad (4)$$

It is desired that the tracking error of the system follow:

$$e_0^{(n)} + k_{n-1} e_0^{(n-1)} + \dots + k_0 e_0 = 0, \quad \text{where}$$

k_i ($i = 1, 2, \dots, n-1$) are the coefficients of the Hurwitz polynomial:

$$H(z) = z^{n-1} + k_{n-1} z^{n-2} + \dots + k_1.$$

In fact, most the parameters and structure of the systems are unknown due to environment changes, modelling errors and unmodelled dynamics. Thus, the primary control law (4) can not be implemented. To solve this problem, the direct adaptive fuzzy control scheme is proposed to approximate the idealized control (4).

3. Direct adaptive Fuzzy Control

In this section, direct adaptive fuzzy control is designed, with guaranteed stability of integrated closed loop system. The direct adaptive controller is designed as follows:

$$u = \hat{u}(\underline{x}, \theta) + u_h + u_s \quad (5)$$

where $\hat{u}(\underline{x}, \theta)$ is the direct adaptive fuzzy control, the auxiliary control u_h is designed to predict the fuzzy approximation error and the influence of the external disturbances, the control u_s is incorporated in the control law in order to ensure the stability and a good tracking error.

The adaptive fuzzy system T-S is used to approximate the primary control action u^* . In the respect, the parameters of the fuzzy control is updated on-line using the Lyapunov approach to guarantee the stability and convergence analysis.

The T-S fuzzy model is described by fuzzy if-then rules, which locally represent linear input-output relations of a system. The fuzzy system is of the following form:

$$R^l : \text{If } x_1 \text{ is } F_1^l \text{ and } x_2 \text{ is } F_2^l \dots, x_n \text{ is } F_n^l \quad (6)$$

then u^l is θ_l

$$l = 1, 2, \dots, m$$

where R^l represents the l th fuzzy inference rule, $x_i, i = 1, \dots, n$ are measurable variables of system, F_i^l denotes fuzzy set. Each fuzzy set F_i^l is associated with a membership function $\mu_{F_i^l}$ and the center of this membership function is the operating



point. By using the weight average fuzzy inference approach [12], we obtain:

$$\hat{u}(\underline{x}, \underline{\theta}) = \frac{\sum_{l=1}^m \prod_{i=1}^n \mu_{F_i^l} \theta_l}{\sum_{l=1}^m \prod_{i=1}^n \mu_{F_i^l}} \quad (7)$$

$$= \underline{\theta}^T \underline{\xi}(\underline{x})$$

$\underline{\theta} = [\theta_1, \theta_2, \dots, \theta_m]^T$ is parameter vector and $\underline{\xi}(\underline{x}) = [\xi_1(\underline{x}), \xi_2(\underline{x}), \dots, \xi_m(\underline{x})]^T$ is a regressive vector with regressor $\xi_l(\underline{x})$ ($1 \leq l \leq m$), (m is the number of rules), which is defined as fuzzy basis function:

$$\xi_l(\underline{x}) = \frac{\prod_{i=1}^n \mu_{F_i^l}}{\sum_{l=1}^m \prod_{i=1}^n \mu_{F_i^l}} \quad (8)$$

The adjustable fuzzy parameters of $\hat{u}(\underline{x}, \underline{\theta})$ are tuned on line using the Lyapunov approach. In order to guarantee that the parameters are bounded, we introduce the projection algorithm [12] to restrict them in the closed set Ω .

$$\dot{\underline{\theta}} = \begin{cases} -\gamma_1 \sigma b \underline{\xi}(\underline{x}) & \text{if } (|\underline{\theta}| < M \text{ or} \\ & (|\underline{\theta}| = M \text{ and } \gamma_1 \sigma b \underline{\theta}^T \underline{\xi}(\underline{x}) > 0)) \\ \text{Proj}[-\gamma_1 \sigma b \underline{\xi}(\underline{x})] & \text{otherwise} \end{cases} \quad (9)$$

$\sigma(\underline{x}, t) = 0$ represents a time varying sliding surface which is defined in the state space R^n by the scalar equation:

$$\sigma(\underline{x}, t) = e_0^{(n-1)} + k_{n-1} e_0^{(n-2)} + \dots + k_1 e_0 \quad (10)$$

where γ_1 is fixed adaptive gain. $\text{Proj}[\cdot]$ represents the projection operator which is defined by:

$$\text{Proj}[-\gamma_1 \sigma b \underline{\xi}(\underline{x})] = -\gamma_1 \sigma b \underline{\xi}(\underline{x}) + \gamma_1 \sigma b \frac{\underline{\theta} \underline{\theta}^T \underline{\xi}(\underline{x})}{|\underline{\theta}|^2} \quad (11)$$

In the practice, however, usually not all states are available, and the hypothesis which consists on considering that the nonlinear dynamics to have the behaviour of the linear combination of known nonlinear functions seems more restrictive, since generally the nonlinear dynamics are completely unknown. Therefore, the prediction of the later is which a great amount of interest in the control nonlinear adaptive control. The fuzzy approximation error and the influence of the external disturbances are estimated by using the orthogonal basis

functions Hermite. This method consists on projecting $w = u - u^*$ and d .

The well known continuous Hermite functions are a basis for the set of polynomials, defined on time domain $]-\infty, +\infty[$, and are given by:

$$S_k(t) = \frac{(-1)^k \exp(-\frac{t^2}{2})}{\sqrt{2^k k! \sqrt{\pi}}} \frac{d^k}{dt^k} \exp(-t^2) \quad (12)$$

Where $k = 0, 1, 2, \dots$ is the function order. These functions can be written in the vector form by defining q the order state vector:

$$S(t) = [S_0(t) \ S_1(t) \ \dots \ S_q(t)]$$

The value at t of any Hermite polynomial S_k can be determined using the following recursion ($0 \leq k \leq q$):

$$S_q(t) = t \sqrt{\frac{2}{q}} S_{q-1}(t) - \sqrt{\frac{q-1}{q}} S_{q-2}(t)$$

Where:

$$S_0(t) = \frac{1}{\sqrt{4\pi}} \exp(-\frac{t^2}{2}), \quad S_1(t) = \frac{\sqrt{2}t}{\sqrt{4\pi}} \exp(-\frac{t^2}{2})$$

Then the control law u_h is derived and based on the Hermite function basis to attenuate the approximation and the influence of the disturbances.

$$u_h = -\varphi S^T(t) \quad (13)$$

The adjustable parameter vector:

$\varphi = [\varphi_1, \varphi_2, \dots, \varphi_q]^T$ is estimated on line using the Lyapunov approach:

$$\dot{\underline{\varphi}} = \begin{cases} -\gamma_2 \sigma b S(t) & \text{if } (|\underline{\varphi}| < N \text{ or} \\ & (|\underline{\varphi}| = N \text{ and } \gamma_2 \sigma b S(t) > 0)) \\ \text{Proj}[-\gamma_2 \sigma b S(t)] & \text{otherwise} \end{cases} \quad (14)$$

The strategy of control u_s is based on SMC approach to ensure stability, tracking and consistent performance:

$$u_s = -k_d \text{sat}(\sigma(\underline{x}, t)) \quad (15)$$

Theorem: Consider the nonlinear system (2). If the direct adaptive fuzzy control (5) is applied with the parameters vector $\underline{\theta}$ and $\underline{\varphi}$ are adjusted by the adaptive law (9)-(14). The closed-loop system is stable in sense that all the signals are bounded and the tracking performance is guaranteed.

Proof:

Consider the following Lyapunov function as:



$$V = \frac{1}{2}\sigma^2 + \frac{1}{2\gamma_1}\Phi\Phi^T + \frac{1}{2\gamma_2}\Psi\Psi^T \quad (16)$$

where

$$\Phi = \theta^* - \theta \text{ and } \Psi = \varphi^* - \varphi$$

The optimal parameters are given by:

$$\theta^* = \arg \min_{\theta \in \Omega_u} \left(\sup_{x \in R^n} |u^* - \hat{u}(x, \theta)| \right) \quad (17)$$

$$\varphi^* = \arg \min_{\varphi \in \Omega_h} \left(\sup_{x \in R^n} |w - \varphi S^T| \right) \quad (18)$$

where $\Omega_u = \{\theta / |\theta| \leq M\}$ and

$\Omega_h = \{\varphi / |\varphi| \leq N\}$ are the convex compact sets

which contain feasible parameter sets for θ and φ .

M and N are pre-specified constants.

$$w = b(\hat{u}(x, \theta^*) - u^*) + d \quad (19)$$

The time derivative of V (16) is:

$$\dot{V} = \sigma \dot{\sigma} + \frac{1}{\gamma_1} \dot{\Phi} \Phi^T + \frac{1}{\gamma_2} \dot{\Psi} \Psi^T \quad (20)$$

$$\dot{\sigma} = x^{(n)} - y_r^{(n)} + \sum_{i=1}^{n-1} k_i e^{(i)} = b(\hat{u}(x, \theta) - u^*) \quad (21)$$

$$-bu_h + bu_s + d(t)$$

$$\dot{V} = \sigma b(\hat{u}(x, \theta) - u^*) - \sigma bu_h + \sigma bu_s + \sigma d(t) + \frac{1}{\gamma_1} \dot{\Phi} \Phi^T + \frac{1}{\gamma_2} \dot{\Psi} \Psi^T \quad (22)$$

$$\begin{aligned} \dot{V} = & \sigma b(\hat{u}(x, \theta) - \hat{u}(x, \theta^*) + \hat{u}(x, \theta^*) - u^*) \\ & - \sigma bu_h + \sigma bu_s + \sigma d(t) + \frac{1}{\gamma_1} \dot{\Phi} \Phi^T + \frac{1}{\gamma_2} \dot{\Psi} \Psi^T \\ \dot{V} = & \sigma b(w + d - u_h + u_s) + \sigma b(\hat{u}(x, \theta^*) \\ & - u^*) + \frac{1}{\gamma_1} \dot{\Phi} \Phi^T + \frac{1}{\gamma_2} \dot{\Psi} \Psi^T \end{aligned} \quad (23)$$

$$\begin{aligned} \dot{V} = & \sigma b(w + d - u_h^* + u_h^* - u_h + u_s) \\ & + \sigma b(\hat{u}(x, \theta^*) - u^*) + \frac{1}{\gamma_1} \dot{\Phi} \Phi^T + \frac{1}{\gamma_2} \dot{\Psi} \Psi^T \end{aligned}$$

Define the minimum approximation error:

$$\varepsilon = w + d - u_h^* \quad (24)$$

The $\dot{V}$ can be written as:

$$\begin{aligned} \dot{V} = & \sigma b(\varepsilon + u_s) + \sigma b(u_h^* - u_h) + \\ & \sigma b(\hat{u}(x, \theta^*) - u^*) + \frac{1}{\gamma_1} \dot{\Phi} \Phi^T + \frac{1}{\gamma_2} \dot{\Psi} \Psi^T \\ \dot{V} = & \sigma b(\varepsilon + u_s) + \sigma b\Psi^T S^T + \sigma b\Phi^T \xi^T + \\ & \frac{1}{\gamma_1} \dot{\Phi} \Phi^T + \frac{1}{\gamma_2} \dot{\Psi} \Psi^T \end{aligned} \quad (25)$$

By consideration of the update laws (9)-(14):

$$\dot{V} = \sigma b(\varepsilon + u_s) + \frac{1}{\gamma_1} \Phi^T (\dot{\Phi} + \sigma b\xi(x)) + \frac{1}{\gamma_2} \Psi^T (\dot{\Psi} + \sigma bS) \quad (26)$$

$$\frac{1}{\gamma_2} \Psi^T (\dot{\Psi} + \sigma bS)$$

Hence

$$\dot{V} \leq |\sigma| (|\varepsilon| - k_d \sigma) \quad (27)$$

So

$$\dot{V} \leq 0$$

4. Simulation Results

In this section, we test the proposed adaptive fuzzy control on the regulation control of the servomechanism. The dynamic equations of the servomechanism can be described in space state as [15]:

$$\begin{cases} \dot{x}_1 = x_2 \\ \dot{x}_2 = f(x, t) + u + d(t) \\ y = x_1 \end{cases} \quad (28)$$

$$f(x, t) = -x_2 - 0.4 \sin(x_1).$$

In the first step, we need to define some fuzzy sets to cover the state space. The choice of the number of fuzzy set and the constant M is related to knowledge of expert on the system. We consider $M = 16$ and three fuzzy membership functions are chosen as in figure 1:

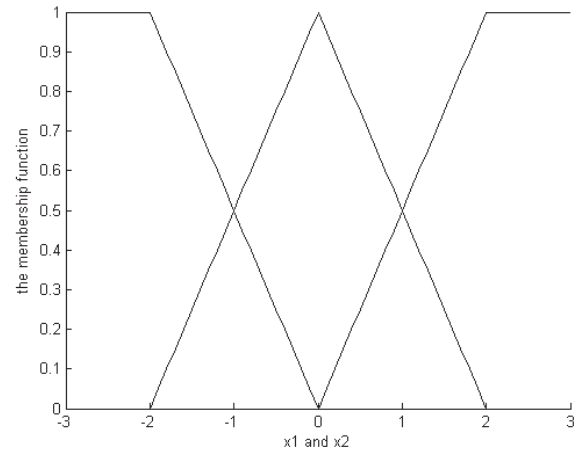


Figure 1: Membership functions

Then there are 9 rules to approximate the primary control law $\hat{u}(x, \theta)$.

The fuzzy rules are defined by the following linguistics description:

$$R^l: \text{If } x_1 \text{ is } F_1^l \text{ and } x_2 \text{ is } F_2^l \text{ then } \hat{u}^l \text{ is } \theta^l \quad (29)$$

Where $l = 1, 2, 3$ and $m = 9$ is the number of the fuzzy rules.



The choice of the number of fuzzy set and the constant M is related to knowledge of expert on the system. The control objective is to maintain the system to track the desired angle

$$\text{trajectory: } y_r = \frac{\pi}{3} * (\sin(0.025t)).$$

The sliding surface is defined as:

$$\sigma(x, t) = k_1 e_0(t) + k_2 \dot{e}_0(t)$$

with $k_1 = 5$ and $k_2 = 1$. The initial consequent parameters $\theta(0)$ of fuzzy control and $\varphi(0)$ are respectively chosen randomly in the interval $[-1, 1]$ and $[-3, 3]$. The fuzzy approximation error and the influence of the external disturbances are predicted using the orthogonal basis of Hermite function

$$S(t) = [S_0(t) \ S_1(t) \ S_2(t)].$$

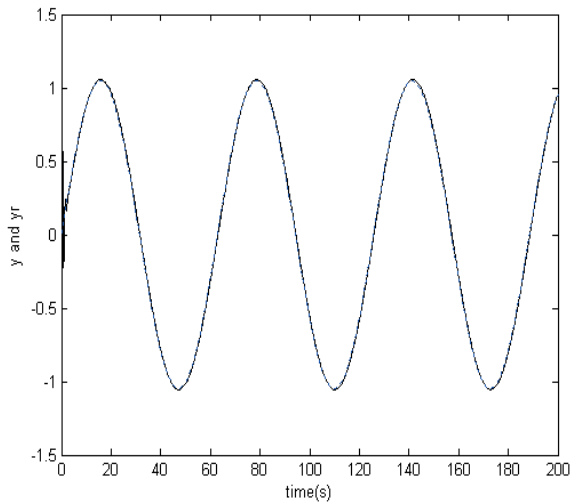


Figure 2: Responses of $y(t)$ and $y_r(t)$

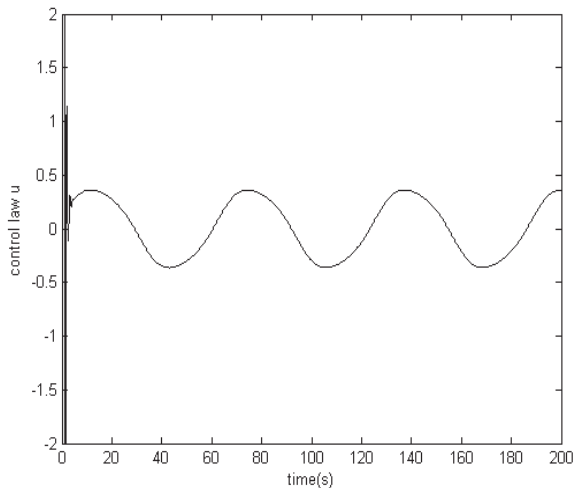


Figure 3: The control signal

Let the learning rate $\gamma_1 = 0.5, \gamma_2 = 0.3$. From figure 2, it can be seen that, the tracking performance is obtained with unknown nonlinear dynamics and in presence of disturbances. The corresponding fuzzy

control signal is given in figure 3. The figures 5 and 6, illustrates the behaviour and the convergence of the parameters of fuzzy control and Hermite function.

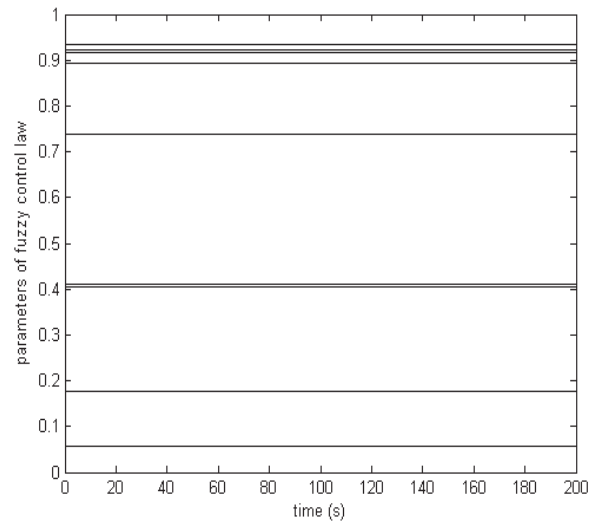


Figure 4: Evolution of θ

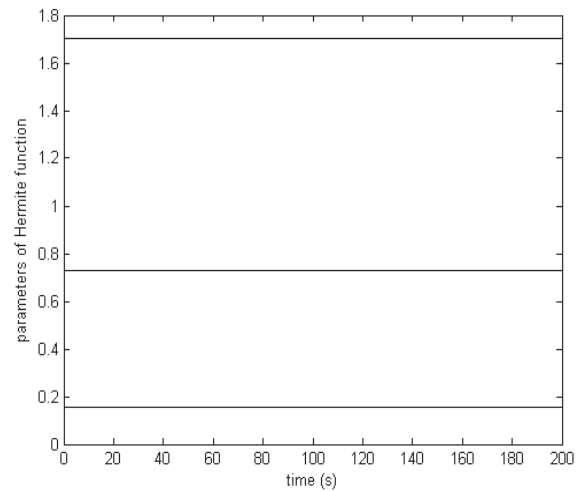


Figure 5: Evolution of φ

5. Conclusion

In this paper, an adaptive fuzzy control has been proposed for a class of unknown nonlinear systems. We introduced the fuzzy system T-S to approximate the part of the primary control. The auxiliary part of control is composed on two terms. The first is incorporated to predict the fuzzy approximation error and the influence of the external disturbances. The synthesis of the second is based on the SMC approach in order to ensure the stability and the tracking performance. The closed loop system is stable in the sense of Lyapunov approach. The simulation results illustrate the effectiveness and robustness of the proposed fuzzy control method.



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